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Research article

A reliable jumping-based classification methodology for environment sector

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A R T I C L E I N F O

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A B S T R A C T

Decision-makers have consistently developed a range of classification models, each possessing unique features within the domain of intelligent models. These endeavors are all directed toward achieving the highest levels of accuracy. In recent developments, two notable methodologies—reliable modeling and jumping modeling approaches—offer specific advantages in formulating cost functions and have been recognized for their role in enhancing classifier accuracy. Specifically, the jumping methodology is based on aligning the learning process with the discrete nature of the classification goal, while the reliable methodology integrates the reliability factor into the learning paradigm. However, their innovative combination, leveraging both accuracy and reliability factors in guiding learning processes, leads to the creation of a high-performing classifier. This addresses a research gap in tackling classification challenges, which remains the core focus of the present study. To evaluate the performance of the proposed reliable jumping-based intelligent classifier in environmental decision-making, we considered ten benchmark datasets spanning various application domains. The numerical results demonstrate that the proposed Reliable Jumping-based intelligent classifier consistently outperforms traditional intelligent classifiers across all studied cases. As a result, the proposed approach proves to be a viable and effective alternative to other intelligent methods in environmental applications.

1. . Introduction

Decision-making in the environmental field has become one of the most challenging areas for scholars, primarily due to the multitude of unknown factors impacting problems, the rapid pace of changes, and increasing complexity. Enhancing the quality of managerial, operational, and strategic choices is of utmost significance for environmental managers and decision-makers. Classification models are recognized as a notable tool in the field of data mining, playing a vital supportive role in environmental-related decision-making. Numerous studies in the machine learning literature have proposed a range of classification methods to address various issues, including monitoring air quality [1] and pollutant emissions [2], water and soil quality [3,4], temperature and humidity forecasting, drought and rainfall prediction [5], identifying landslides [6] and floods [7], managing river streamflow and runoff [8], solid waste management [9], and water resources management, among others. Some of these well-established approaches include Logistic Regression (LR), Naïve Bayes (NB), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Artificial Neural Networks (ANNs), Multilayer Perceptrons (MLPs), Support Vector

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Machines (SVMs), Decision Trees (DT), Random Forests (RF), Light Gradient Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Deep Belief Neural Networks (DBNN).

A fundamental consideration for decision-makers across various fields and environments is selecting the most accurate classification model [54]. The classification literature encompasses a wide range of research endeavors aimed at enhancing the accuracy of various classifier types. These investigations include methods for data preprocessing and feature selection, optimization algorithms to improve the learning procedure, as well as the hybridization of multiple individual classifiers to leverage their strengths, among other techniques. The paper's workflow is outlined in Fig. (1).

The following summarizes some research initiatives aimed at enhancing classifier performance through the utilization of optimization and/or pre-processing methods. Hong et al. [25] introduced an MLP network to categorize landslide-susceptible regions in China. They employed Gradient Descent (GD) and the Genetic Algorithm (GA) to determine the connection weights of this model. The results demonstrated that their approach outperformed the RF and LR methods. Qiao et al. [26] proposed an optimization-based learning approach, utilizing a modified whale optimization algorithm to train MLP for classifying underwater targets. The results demonstrated that their proposed model outperformed MLPs trained using the grey wolf optimization and biogeography-based optimization methods. Belghit et al. [27] developed a classification approach for categorizing precipitation intensities that includes SVM as a classifier and AdaBoost as an optimizer. Albarico et al. [28] evaluated the classification abilities of SVM, RF, ANN, and multinomial LR, each equipped with various pre-processing steps including scaling, outlier removal, and synthetic minority oversampling techniques. The study demonstrated that RF outperformed the other models in classifying the most suitable greenhouse

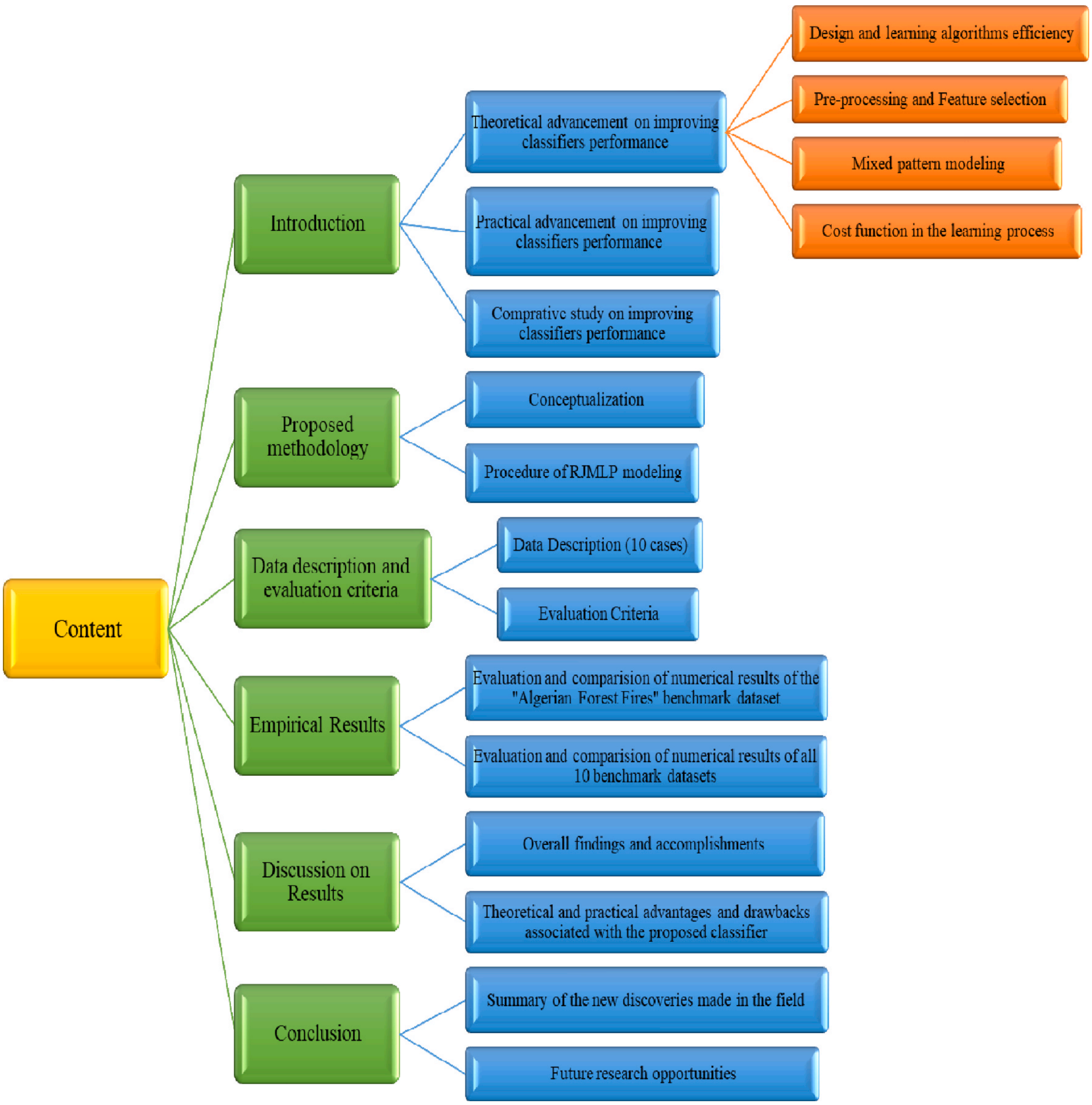

Fig. 1. Workflow of paper.

environment conditions for optimal rose cultivation. Du et al. [8] predicted changes in runoff response for water resource management using RF and CUBIST models, which employed Principal Component Analysis (PCA) as a pre-processing technique. The CUBIST model exhibited better performance than RF.

However, other studies have utilized feature selection algorithms. The purpose of these algorithms is to identify valuable features while eliminating redundant ones, all aimed at enhancing the discriminative abilities of the classifiers. Nafouanti et al. [29] conducted a performance comparison of pre-processing-based LR, RF, and ANN classifiers to assess groundwater quality. To enhance the accuracy of the classifiers, they implemented the chi-squared feature selection technique to identify the most informative inputs. Based on the performances achieved by these classifiers, RF outperformed both the ANN and LR models. Ferreiro et al. [30] assessed the performance of KNN, LDA, and Quadratic Discriminant Analysis (QDA), all of which utilized GA for feature selection. The study revealed that KNN demonstrated higher accuracy than LDA and QDA in identifying pollution caused by plastics. Hamami and Dahlan [1] applied various machine learning models, including DT, LR, KNN, and RF, to determine air quality by classifying pollutant concentrations. These models were equipped with pre-processing techniques for feature selection and data cleaning. The research illustrated that DT outperformed the other models in air quality monitoring.

Furthermore, some scholars have undertaken studies to develop hybrid approaches that leverage the classification capabilities of multiple individual classifiers. Piaser and Villa [31] conducted an evaluation of several single models, including SVM, ANN, KNN, DT, and NB, as well as ensemble classifiers such as XGBoost, RF, and boosted decision tree (C5.0), for the classification of aquatic vegetation. Additionally, they investigated the effects of varying the number of input features on the accuracy of these classifiers. The research emphasized the superior performance of ensemble models compared to individual ones, with the exception of SVM.

Table 1
Recent papers on environmental classification using intelligent classifiers.

Author(s)/[Ref.]	Year	Classifier(s)	Application	Description/Outcomes
Kim et al. [10]	2024	Deep learning model, U-Net	Surface sediment classification	The proposed model exhibited superior performance compared to both the decision tree and maximum likelihood algorithm.
Macreadie et al. [11]	2024	XGBoost	Forecasting carbon levels in marine sediment	Based on empirical results, the model can be effectively implemented in environmental settings, particularly for quantifying the proportions of macroalgal carbon among other carbon sources in sediment samples.
Dai et al. [12]	2024	Lightweight deep-learning model	Plant disease classification	Establishing multi-level deep information feature fusion extraction network to achieve accurate results.
Sahu et al. [13]	2024	CNN	Mapping and classification of surface cover types	Developing a pre-processing-based three-layered max-pooling convolutional neural network for observing the Earth's environment.
Meng et al. [14]	2024	CNN	Monitoring and assessing the quality of water resources	Proposing a CNN based on AlexNet and utilizing correlation analysis, redundancy analysis, and the RF method to classify lake water quality for aquatic ecosystems.
Wu et al. [15]	2024	SVM, KNN, LDA, PLS-DA, backpropagation neural network	Categorizing different types of plastics for recycling purposes	Based on empirical results, the performance of SVM and Partial Least Squares Discriminant Analysis (PLS-DA) was superior to that of other classifiers.
Do et al. [16]	2024	XGBoost, ABC-ANFIS	Forest cover classification and forest fire mapping	Developing XGBoost for classifying forest types and utilizing the Artificial Bee Colony-Adaptive Neuro-Fuzzy Inference System (ABC-ANFIS) for assessing forest fire susceptibility.
Flores et al. [17]	2024	RF	Reproductive conditions identification	Using Random Forest for classifying various reproductive conditions in fish.
Zhang et al. [18]	2023	CNN-DBNN	Solid waste classification	Establishing a classification method involving a pre-processing step, CNN for feature extraction, and DBNN as a prediction model. The proposed model exhibited superior performance compared to CNN-MLP, LightGBM, LSTM, and ensemble models.
Carrera et al. [19]	2023	LR, SVM, and other machine-learning algorithms	Classification of recycled plastic materials	Evaluating the effectiveness of various classifiers, including LR, SVM, and other machine learning algorithms, to identify the most suitable classifier. Pre-processing methods, such as replacing missing data, noise reduction, and rectification, were applied to enhance classifier performance.
Li and Chen [20]	2023	CNN and Graph-LSTM	Municipal solid waste classification	Introducing a hybrid framework that utilizes both CNN and Graph-LSTM models, along with pre-processing techniques.
Chen et al. [21]	2023	ShuffleNet v2- depth-separable convolution model	Recyclable waste classification	Formulating a combined classification approach based on ShuffleNet v2 and the depth-separable convolution model, enabling efficient classification of recyclable waste.
Tasnim et al. [22]	2023	Deep learning	Pollutants associated with textiles	Introducing an advanced deep learning classifier called EfficientNet, which outperformed KNN and CNN models in detecting and categorizing visual pollutants associated with textiles, including cloth waste, dyeing materials, and advertising displays.
Luo et al. [23]	2023	CNN	Weed seeds classification	Investigating various CNN model structures to determine the most effective approach for classifying weed seeds.
Bellamoli et al. [24]	2023	MLP, SVM, RF, XGBoost, and LightGBM	Classifying anomalies in wastewater treatment processes	Comparing the performance of MLP, SVM, RF, XGBoost, and LightGBM in classifying anomalies in wastewater treatment processes. The results indicate that gradient-boosting methods outperformed other classifiers.

Furthermore, reducing the number of input features resulted in a decrease in classification accuracy, but RF was less affected than SVM. Sahana et al. [32] examined different hybrid methods for MLPs, including dagging, bagging, and decorating, for forecasting rainfall-induced landslide susceptibility in India. The study highlighted the superior performance of bagging-MLP compared to other configurations. Kim et al. [2] developed a classification strategy that incorporates PCA as a pre-processing technique for dimension reduction of inputs. They utilized MLP and CNN as classifiers to accurately classify the concentration of CO and NO2 mixtures.

Moreover, additional efforts have been made to develop novel classification models and achieve further advancements. Jin et al. [33] created an enhanced deep learning model, MobileNetV2, for garbage detection and classification, ultimately contributing to environmental pollution management. They accomplished this by implementing transfer learning with pre-trained weight parameters and incorporating PCA to reduce the model's parameters. Wang et al. [34] introduced a combination of localized spatio-temporal association analysis and LR to predict urban growth based on existing land cover configurations. Guo et al. [35] utilized a two-level KNN classifier to identify invasive plants, achieving superior performance compared to CNN models. The outcomes of this study proved effective in safeguarding the ecosystem.

A significant portion of research in the environmental field focuses on the practical application of various machine learning approaches within specific datasets or domains. The primary objective and consistent outcome of these studies is to demonstrate that the model under consideration can effectively serve as a viable option for modeling, often achieving the desired level of accuracy. Amato et al. [6] utilized the MLP classifier to categorize types of landslides. They emphasized that MLP can produce accurate outcomes, and the insights from their study can provide guidance for preserving aesthetic values to enhance tourism appeal. Saeidi et al. [39] assessed and confirmed the superiority of the MLP network over LR in mapping landscape aesthetics within the Ziarat watershed basin in northeastern Iran. Hakim et al. [40] employed the MLP network to classify land use conversions in Indonesia. They indicated that the MLP can yield the desired outcomes, and the model's results can support the development of sustainable urban areas. Handayani et al. [41] utilized SVM to identify air pollution in urban areas, using data from sensor readings including PM10, CO, CO2, HC, and other indices, along with temperature data. Chola and Benifa [42] employed the CNN model to categorize sunspots, and the findings of this study have potential applications in specifying space weather and its impact on Earth's environment. Billah et al. [43] assessed flood damage using the RF classifier, which outperformed the maximum likelihood classification model across various land classes. Moreover, Yang et al. [44] developed an LR model for evaluating the vulnerability of storage tanks to floods. They assessed and validated this model using Receiver Operating Characteristic (ROC) curves. The results provided valuable insights for effective crisis management.

Clearly, none of the previously mentioned classification models can be regarded as a universally superior classifier with guaranteed accuracy surpassing all others. Consequently, some studies have highlighted the effectiveness and higher accuracy of a classifier for specific applications compared to other model types. Verslype et al. [50] evaluated and compared the effectiveness of XGBoost, SVM, RF, DT, KNN, and LDA in predicting the drought tolerance classes of grapevine rootstocks. The study revealed that RF emerged as the top-performing classifier, followed by XGBoost. Shaziayani et al. [51] compared and evaluated the performance of RF, DT, and boosted regression trees to determine the superior model for classifying PM10 concentration. The numerical findings highlighted the superior

Table 2
Summary of the literature review for environmental classification based on development categories.

Category	Sub-Category	References	Classifier(s)	Application
Theoretical	Design and learning algorithms efficiency	[25–27]	MLP, MLP, SVM	Identification and categorization of regions prone to landslides, Underwater target classification, Precipitation intensity classification
	Pre-processing and Feature selection	[1,8,28–30]	RF, CUBIST, RF, KNN, DT	Classification of environmental conditions within greenhouses, Forecasting changes in runoff patterns, Identification and characterization of groundwater quality, Detection and assessment of pollution caused by plastics, Pollutant concentration classification
	Mixed pattern modeling	[2,31,32]	ensemble models (XGBoost, RF), a hybrid of MLPs, MLP-CNN	Categorization of underwater plant species, Forecasting the likelihood of landslides triggered by rainfall, Classifying the concentration levels of CO and NO2 mixtures
	Other advancements	[33–35]	MobileNetV2, LR, KNN	Garbage detection and classification, Urban growth prediction, Identification of invasive plants
	Cost function in the learning process	[36–38]	(LR, MLP, DMLP); MLP; (LR, MLP; DMLP)	Management of energy sources and consumption, (Medicine, finance, energy, engineering, environment, transportation), Cancer and disease diagnosis
Practical		[6,39–44, 45–49]	MLP, MLP, MLP, SVM, CNN, RF, LR, ANN, RF, CNN, NB, LR	Classification of different forms of landslide events, Assessment of the visual quality of landscapes, Categorization of changes in land use patterns, Detection and classification of various air pollutants, Classifying sunspots, Assessing flood damage, Assessing flood damage, Categorization of diseases affecting potato plants, Classification of deterioration in coastal wetland ecosystems, Identification of diseases affecting plant leaves, Categorizing samples of wastewater influent, Evaluation of the effectiveness of ecological technologies
Comparative study		[50–53]	(XGB, SVM, RF, DT, KNN, LDA); (RF, DT, boosted regression trees); (RF, DT); (CNN, LSTM)	Predicting drought, Categorizing levels of PM10 concentration, Identifying emission sources of odorous substances, Classification of the severity of methane leaks

classification ability of RF compared to the other two classifiers. Choi et al. [52] assessed the performance of RF and DT in identifying odorant emission sources in urban areas. The empirical results indicated that the RF classifier, even when utilizing fewer explanatory variables, successfully detected all emission sources and outperformed DT. Wang et al. [53] evaluated the effectiveness of 2D and 3D CNNs, as well as Convolutional LSTM models, for categorizing methane leak size from the natural gas system. According to empirical evidence, the 3D CNN classifier exhibited the highest level of accuracy compared to the other two models. Some recently published papers in the field of environmental-related classification issues using intelligent classifiers are provided in Table 1.

Despite all the developments aimed at achieving acceptable accuracy in both shallow and deep classifiers, ongoing efforts to enhance their performance remain a persistent topic in the literature. Recently, two impactful modeling methodologies with distinct characteristics have emerged, and their ability to enhance accuracy across a range of classifiers has been verified. These methodologies are known as reliable and jumping modeling strategies. The jumping-based learning outlines a navigation strategy for each learning stage by allowing solely discrete values for the target variable instead of continuous changes. Indeed, the jumping-based approach excels by adapting its learning paradigm to the discrete nature of the classification objective, outperforming alternative methods that rely on other types of cost functions [36]. The reliability-based approach directs its attention toward improving the classifier's ability to generalize, achieved by introducing a novel cost function based on the concept of reliability. The primary objective is to minimize performance variations across different data points. As a result, the reliability methodology excels in performance by strengthening the learning process, distinguishing itself from the accuracy-based approach that primarily strives to maximize accuracy on training data [37,38]. While these two methodologies have distinct foundational concepts, they share similar modeling processes and both emphasize cost/loss functions, making it possible to use them in combination. However, existing research in the classification field shows that they haven't been simultaneously applied in any classifier. The summary of the mentioned literature review for environmental classification purposes based on their category of development is presented in Table 2.

Therefore, this paper introduces an innovative strategy called the Reliable Jumping-Based Multilayer Perceptron (RJMLP), merging the advantageous characteristics of two reliable and jumping methods to enhance the classification performance of multilayer perceptron classifiers. The procedure begins by employing the jumping approach to select the mismatching function, transforming the continuous set into a discrete form. Subsequently, the reliable method is utilized to enhance jumping-based learning by minimizing variations in the mismatching function during the learning process. In the present paper, Multilayer Perceptrons (MLPs), which are among the most widely used classifiers, have been selected, and the proposed methodology is applied to environmental decision-making. However, this is a general classification methodology that can be applied to both shallow and deep intelligent classifiers. Additionally, it can serve as a valuable decision-making tool across various disciplines such as medicine, finance, transportation, engineering, energy and renewable energy, and management.

The principal hypotheses/questions of the study can be stated as follows:

1) Can the proposed reliable-jumping cost function effectively replace conventional methods?
2) Is it possible for the proposed reliable-jumping learning algorithm to demonstrate greater efficiency compared to its conventional counterparts?
3) Can the proposed reliable-jumping multilayer perceptron achieve higher accuracy compared to the conventional MLP model?

To assess and confirm the effectiveness of the proposed RJMLP, we utilized 10 benchmark datasets in the environmental field. This evaluation involves comparing the performance of the RJMLP classifier with conventional models. In summary, the novelty of this study can be outlined as follows:

➢ The paper introduces a novel reliable-jumping learning process, which is built upon the principles of discrete and reliability-based learning. This approach leverages both accuracy and reliability factors, specifically designed for classification problems.
➢ The central concept of the proposed approach is to adjust the training procedure of classifiers to accommodate the discrete form of classification, thereby achieving high accuracy in results.
➢ The suggested approach integrates the reliability concept into the learning paradigm to enhance the classifier's capacity to generalize the high level of accuracy achieved during the training phase to the testing phase.
➢ The performance evaluation of the proposed methodology against traditional multilayer perceptrons and some commonly used statistical and intelligent classifiers, both shallow and deep, single and hybrid, is conducted using one benchmark dataset. Moreover, a comparative analysis of the proposed methodology against traditional LR, MLP, and SVM classifiers is carried out using nine other benchmark datasets with various applications in the environmental field.

The structure of the paper for the remainder is as follows: Section 2 introduces the concepts and formulation of the proposed Reliable Jumping-based Multilayer Perceptron (RJMLP). Section 3 describes the benchmark datasets in the environmental field and the criteria used for evaluation. In Section 4, we examine the performance of the RJMLP classifier in selected case studies, comparing it with the traditional version and other commonly used classifiers. Section 5 discusses the overall findings and accomplishments of the study. Lastly, Section 6 presents the conclusions.

2. . Proposed Intelligent Reliable Jumping (IRJ) methodology

This section presents an overview of the conceptualization, formulation, and procedure of the proposed Intelligent Reliable Jumping (IRJ) methodology designed for classification problems. In the first subsection, the idea and concept of the proposed methodology are elaborated upon. Following that, the formulation of the proposed classifier is proposed.

2.1. . Conceptualization

Multilayer Perceptron (MLP) classifiers possess distinct characteristics, including flexible nonlinear modeling, universal approximation, and self-adaptive data-driven procedures. These traits grant them exceptional capacity to effectively model uncertain, intricate, and mixed patterns with remarkable accuracy, setting them apart from other shallow intelligent classifiers [55]. Consequently, MLP classifiers stand out as one of the most potent approaches in machine learning for addressing classification problems. However, the literature includes a plethora of research and studies aimed at mitigating the drawbacks of MLPs while reinforcing their merits. These efforts aim to maximize the accuracy of this type of classifier as much as possible. In this regard, two of the most recently introduced methodologies have been proven to be remarkable in boosting classifier accuracy. This achievement stems from their utilization of procedures grounded in the concepts of reliability and jumping. These methodologies establish novel cost functions, resulting in highly effective learning procedures. In other words, these two methodologies demonstrate an outstanding ability to outperform their traditional counterparts, showcasing their efficacy in tackling classification, diagnosis, and pattern recognition challenges.

Specifically, the jumping methodology utilizes a discrete loss function. This strategy ensures that, at every stage of the learning process, the variables can only move in either a positive or negative direction compared to the preceding step, leading to the attainment of discrete points. In this way, the final learning step produces discrete values as output, aligning with the discrete nature of classification problems. Consequently, by benefiting from this conformity and avoiding the rounding process of the output of the classifier to discrete values, the jumping methodology outperforms classifiers that employ continuous or semi-continuous loss functions in terms of accuracy [56]. On the other hand, the reliable methodology focuses on constructing a cost function grounded in the concept of reliability, guiding the learning process to minimize variation between performance criteria as much as possible. Consequently, it emerges as a promising approach, as it maintains model stability when the training data points are altered, ultimately resulting in the development of a classifier with strong generalizability [57]. To clarify, incorporating the reliability factor into the learning paradigm can strengthen the classifier's ability to generalize the high level of accuracy attained during the training phase to the testing phase. Of significant note is that the reliable methodology holds universal applicability and can be utilized with various types of loss functions. This versatility results in classifiers that incorporate reliable versions of these loss functions.

However, the combination of reliability and jumping approaches not only provides distinct advantages in designing cost functions and guiding learning procedures but also results in the development of a reliable jumping classifier with superior accuracy. This innovative approach represents a new advancement in addressing classification problems, which is the primary focus of the current study. Accordingly, during the initial stage of the proposed RJMLP methodology, the jumping-based approach is employed to modify the cost/loss function of conventional MLP classifiers. This adaptation involves transforming the continuous feasible set into a discrete one, enabling the MLP model to navigate through these discrete points effectively. In the second phase, the reliable-based methodology is applied to the jumping-based cost/loss function derived from the preceding stage. As a result, the connection weights of the classifier are estimated in a manner that minimizes their jumping frequency.

2.2. . Procedure of reliable jumping-based multilayer perceptron (RJMLP) modelling

The Multilayer Perceptron (MLP), being one of the most popular and commonly applied types of intelligent methods, has been chosen to implement the proposed Reliable Jumping methodology. Typically, the binary classification model of MLP, comprising a dependent variable $Y \in \{-1, +1\}$ and M explanatory variables $X_1, X_2, \ldots, X_M \in \Re$, can be denoted as follows:

$$Y_t = f\left(\beta_0 + \sum_{j=1}^{p} \beta_j . g\left(\beta_{0j} + \sum_{i=1}^{m} \beta_{i,j} . X_{t,i}\right)\right) + u_t \qquad t = 1, 2, 3, \ldots, N \tag{1}$$

In the equation, β_j, β_{ij} corresponds to the connection weight between the neurons in the model. Additionally, g and f represent the activation functions for the hidden and output layers, respectively, u_t is the stochastic disturbance term, while N denotes the sample size.

The RJMLP classifier is meticulously designed with a sequence of steps. **Initially**, the input data is partitioned into three distinct sets: training, validation, and testing. **Next**, the jumping methodology is applied to the training and validation data, selecting the mismatching criteria as the loss function. This choice governs the navigation method during each epoch of the training and validation phases, involving jumps to discrete points. In essence, the learning process relies on discrete movements of estimated values, instead of the continuous or semi-continuous methods of navigation [36]. Accordingly, $Mismatch(y_t, \hat{y}_t)$ serves as the mismatching function between the actual ($y_t \in \{-1, +1\}$) and fitted ($\hat{y}_t \in \Re$) values at time t, and its representation is in binary form as follows:

$$Mismatch(y_t, \hat{y}_t) = \begin{cases} -1 & if \;\; (y_t)(\hat{y}_t) \geq 0 \\ +1 & if \;\; (y_t)(\hat{y}_t) < 0 \end{cases} \tag{2}$$

Finally, the reliable methodology is put into action. Initially, the mismatching criterion is computed for the training data. Subsequently, the first validation data is integrated into the training pool, and the mismatching criterion is recalculated. This iterative process is repeated n times, eventually resulting in the calculation of the mismatching criterion based on both the training and all validation data points. To achieve a reliable version of jumping-based MLP, the mismatching errors should be approximately equal to each other at each stage [57], as indicated by Eq. (3), based on the validation data points.

$$Mismatch(y_k, \widehat{y}_k) \cong Mismatch(y_{k'}, \widehat{y}_{k'}) \quad \forall k, k' \quad k, k' \in n \quad k \neq k' \tag{3}$$

Now, Eq. (3) can be represented as follows:

$$nMismatch(y_1, \widehat{y}_1) \cong Mismatch(y_1, \widehat{y}_1) + Masmatch(y_2, \widehat{y}_2) + \ldots + Mismatch(y_n, \widehat{y}_n) \tag{4}$$

Then, Eq. (4) can be rewritten using the *Sign* function as follows:

$$-n\sum_{t=1}^{N}\left((y_t).Sign\left(f\left(\widehat{\beta}_{01} + \sum_{j=1}^{p}\widehat{\beta}_{j1}.g\left(\widehat{\beta}_{0j1} + \sum_{i=1}^{m}\widehat{\beta}_{ij1}.X_{i,t}\right)\right)\right)\right) \cong -\sum_{k=0}^{n} \times \sum_{t=1}^{N+k}\left((y_t).Sign\left(f\left(\widehat{\beta}_{0k} + \sum_{j=1}^{p}\widehat{\beta}_{jk}.g\left(\widehat{\beta}_{0jk} + \sum_{i=1}^{m}\widehat{\beta}_{ijk}.X_{i,t}\right)\right)\right)\right) \tag{5}$$

The Reliable Jumping-based Multilayer Perceptron (RJMLP) can be constructed by minimizing the discrepancies between each pair of mismatching errors across all validation data points. This concept is mathematically represented by Eq. (6).

$$Min\left(\begin{array}{l} n\sum_{t=1}^{N}\left((y_t).Sign\left(f\left(\widehat{\beta}_{01} + \sum_{j=1}^{p}\widehat{\beta}_{j1}.g\left(\widehat{\beta}_{0j1} + \sum_{i=1}^{m}\widehat{\beta}_{ij1}.X_{i,t}\right)\right)\right)\right) - \\ \sum_{k=0}^{n}\sum_{t=1}^{N+k}\left((y_t).Sign\left(f\left(\widehat{\beta}_{0k} + \sum_{j=1}^{p}\widehat{\beta}_{jk}.g\left(\widehat{\beta}_{0jk} + \sum_{i=1}^{m}\widehat{\beta}_{ijk}.X_{i,t}\right)\right)\right)\right) \end{array}\right) \tag{6}$$

The reliable methodology integrates the reliability factor into the jumping-based learning process to strengthen the jumping-based classifier. This enhancement aims to maximize the generalization of high accuracy achieved during the training phase to the testing

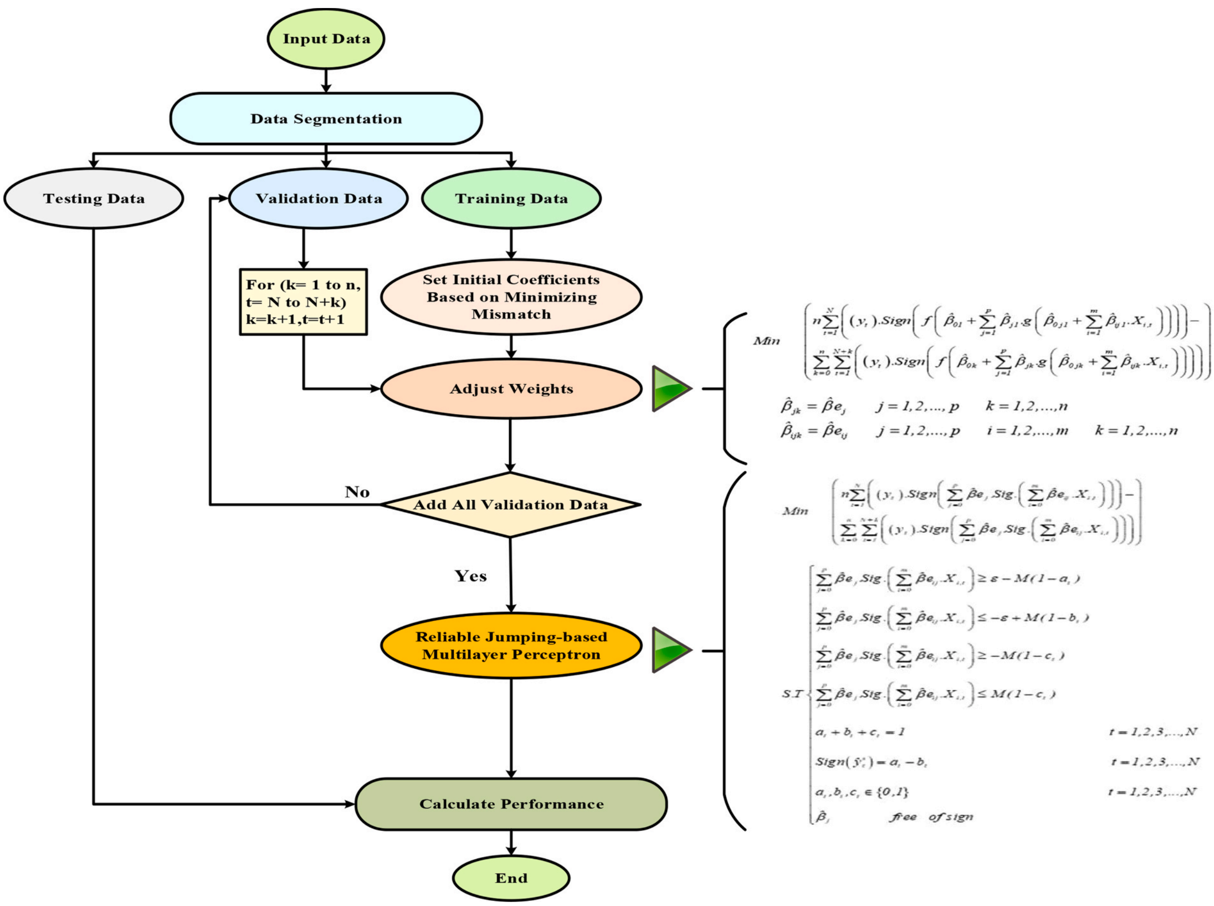

Fig. 2. Flowchart illustrating the procedure of Reliable Jumping-based Multilayer Perceptron (RJMLP) Modelling.

phase. Therefore, to acquire the RJMLP classifier with minimal uncertainty, it is crucial to replace the unknown weights of all JMLP with reliability-based weights, as demonstrated in Eq. (7).

$$\begin{aligned} \widehat{\beta}_{jk} &= \widehat{\beta}e_j \quad j = 1, 2, \ldots, p \quad k = 1, 2, \ldots, n \\ \widehat{\beta}_{ijk} &= \widehat{\beta}e_{ij} \quad j = 1, 2, \ldots, p \quad i = 1, 2, \ldots, m \quad k = 1, 2, \ldots, n \end{aligned} \tag{7}$$

$\widehat{\beta}e_{ij}, \widehat{\beta}e_j$ represent the connection weights of RJMLP. Additionally, the sigmoid function (Sig.) and linear function are adopted as the hidden and output transfer functions, respectively. Consequently, the reliable jumping cost function can be mathematically established for the Multi-Layer Perceptron. This methodology involves adopting mixed-integer nonlinear programming as the cost function, as described in Eq. (8), to ascertain the unknown connection weights of the RJMLP classifier. Where, ε and M are very small and very large numbers, respectively. The graphical representation of the RJMLP modeling procedure is shown in Fig. (2).

$$\begin{aligned} & Min \left(\begin{array}{l} n\sum_{t=1}^{N}\left((y_t).Sign\left(\sum_{j=0}^{p}\widehat{\beta}e_j.Sig.\left(\sum_{i=0}^{m}\widehat{\beta}e_{ij}.X_{i,t}\right)\right)\right) - \\ \sum_{k=0}^{n}\sum_{t=1}^{N+k}\left((y_t).Sign\left(\sum_{j=0}^{p}\widehat{\beta}e_j.Sig.\left(\sum_{i=0}^{m}\widehat{\beta}e_{ij}.X_{i,t}\right)\right)\right) \end{array} \right) \\ & S.T \begin{cases} \sum_{j=0}^{p}\widehat{\beta}e_j.Sig.\left(\sum_{i=0}^{m}\widehat{\beta}e_{ij}.X_{i,t}\right) \geq \varepsilon - M(1-a_t) \\ \sum_{j=0}^{p}\widehat{\beta}e_j.Sig.\left(\sum_{i=0}^{m}\widehat{\beta}e_{ij}.X_{i,t}\right) \leq -\varepsilon + M(1-b_t) \\ \sum_{j=0}^{p}\widehat{\beta}e_j.Sig.\left(\sum_{i=0}^{m}\widehat{\beta}e_{ij}.X_{i,t}\right) \geq -M(1-c_t) \\ \sum_{j=0}^{p}\widehat{\beta}e_j.Sig.\left(\sum_{i=0}^{m}\widehat{\beta}e_{ij}.X_{i,t}\right) \leq M(1-c_t) \\ a_t + b_t + c_t = 1 \quad t = 1, 2, 3, \ldots, N \\ Sign\left(\widehat{y}_t^s\right) = a_t - b_t \quad t = 1, 2, 3, \ldots, N \\ a_t, b_t, c_t \in \{0, 1\} \qquad t = 1, 2, 3, \ldots, N \\ \widehat{\beta}_j \quad free \quad of\, sign \end{cases} \end{aligned} \tag{8}$$

3. . Data description and evaluation criteria

In this study, the effectiveness of the proposed Reliable Jumping methodology has been evaluated by employing 10 benchmark datasets from the environmental field. These datasets encompass applications such as air quality monitoring, temperature forecasting, forest ecosystem analysis, forest fire detection, and vegetation classification. These datasets are publicly available, sourced from the UCI website [58]. They involve sample sizes ranging from 244 to 41,757 and variable counts from 5 to 27. The data were collected between 2008 and 2020 years. Detailed information about these datasets is included in Table 3.

Table 3
The characteristics of the benchmark datasets from the UCI database.

No.	Name	Year	Sample size	Number of explanatory variables	Characteristics of Attributes	Scope
1-	Forest fires	2008	517	12	Real	Determining the forest fire region
2-	SML 2010	2014	4137	20	Real	Forecasting air temperature
3-	Numerical prediction model temperature	2020	7588	23	Real	Forecasting air temperature
4-	$PM_{2.5}$ of Five Chinese Cities	2017	20166	13	Integer, Real	Air quality assessment
5-	Beijing $PM_{2.5}$ Data	2017	41757	11	Integer, Real	Air quality assessment
6-	Beijing Multi-Site Air-Quality Data	2019	32907	15	Integer, Real	Air quality assessment
7-	Occupancy Detection	2016	20560	5	Real	Evaluating air condition
8-	Wilt	2014	4839	5	Real	Classifying plant cover
9-	Forest type mapping	2015	523	27	Real	Quantifying the ecosystem services provided by the forest
10-	Algerian Forest Fires	2019	244	7	Real	Identifying forest fire

- ***Algerian Forest Fires:*** This benchmark dataset consists of 244 samples with 7 real attributes, including maximum temperature, relative humidity, wind speed, rain, duff moisture code index, drought code index, and buildup index from the FWI system. The data is classified into two categories: fire or no fire, based on these attributes, with class rates of 56.56 % and 43.44 %, respectively.
- ***Forest Type Mapping:*** This dataset comprises 523 instances and 27 attributes, focusing on quantifying the ecosystem services provided by the forest. The attributes include detailed information about b1 to b9, pred-minus-obs-H-b1 to pred-minus-obs-H-b9, and pred-minus-obs-S b1 to pred-minus-obs-S-b9. The data is classified into two classes: Sugi and Hinoki forest or mixed deciduous and other forest, based on these attributes, with class rates of 53.73 % and 46.27 %, respectively.
- ***Wilt Dataset:*** This dataset comprises 4,839 samples and 5 attributes, all of which are real values. These attributes include information about GLCM mean texture (panchromatic band), mean green value, mean red value, mean NIR value, and standard deviation (panchromatic band). The levels of these factors and indices classify land cover into diseased trees or healthy, with class rates of 94.61 % and 5.39 %, respectively.
- ***Occupancy Detection:*** This benchmark dataset comprises a total of 20,560 instances. These instances involve 5 real attributes, namely temperature, relative humidity, light, carbon dioxide, and humidity ratio, which determine room air condition. The classification of the air condition as desirable or not desirable is based on the levels of these factors and indices. The data is divided into two classes: desirable or not-desirable, based on these attributes, with class rates of 76.90 % and 23.10 %, respectively.
- ***Forest Fires:*** This benchmark dataset comprises 517 instances, each featuring 12 real attributes that determine the forest fire region. These attributes include x-axis spatial coordinate, y-axis spatial coordinate, month, day, FFMC index, DMC index, DC index, and ISI index from the FWI system, as well as temperature, relative humidity, wind speed, and outside rain. The data is categorized into two classes based on these factors, with class rates of 60.35 % and 39.65 %.
- ***The SML 2010:*** This benchmark dataset comprises 4,137 instances, featuring 20 real attributes that determine weather temperature. These attributes include date, time, dining room temperature, room temperature, dining room carbon dioxide, room carbon dioxide, dining room relative humidity, room relative humidity, dining room lighting, room lighting, rain, sun dusk, wind, sunlight in the west facade, sunlight in the east facade, sunlight in the south facade, sun irradiance, outdoor temperature, outdoor relative humidity, and day of the week. The data is categorized into two classes, low temperature and high temperature, based on these factors, with class rates of 55.14 % and 44.86 %, respectively.
- ***Numerical prediction model temperature:*** This dataset comprises 7,588 instances, with 23 real attributes determining the next-day air temperature. These attributes include station, date, present maximum air temperature, present minimum air temperature, minimum relative humidity, maximum relative humidity, LDAPS-temperature max-lapse, LDAPS-temperature min-lapse, next-day average wind speed, next-day average latent heat flux, next-day average cloud cover (1st 6-h to 4th 6-h), next-day average precipitation (1st 6-h to 4th 6-h), latitude, longitude, elevation, slope, and solar radiation. The data is classified into two classes, low and high temperature, based on these factors, with class rates of 47.96 % and 52.04 %, respectively.
- ***PM2.5 of Five Chinese Cities:*** This benchmark dataset comprises 20,166 instances, with 13 real-integer attributes determining the level of air pollution (PM2.5 concentration). These attributes include year, month, day, hour, season, dew point, humidity, pressure, temperature, combined wind direction, cumulated wind speed, hourly precipitation, and cumulated precipitation. The combination of these factors determines whether the air quality is healthy or unhealthy, with class rates of 62.08 % and 37.92 %, respectively.
- ***Beijing PM2.5 Data:*** This benchmark dataset comprises 41,757 instances, with 11 real-integer attributes determining PM2.5 concentration. These attributes include year, month, day, hour, dew point, temperature, pressure, combined wind direction, cumulated wind speed, cumulated hours of snow, and cumulated hours of rain. The combination of these factors determines whether the air quality is healthy or unhealthy, with class rates of 62.31 % and 37.69 %, respectively.
- ***Beijing Multi-Site Air-Quality Data:*** The Beijing air quality benchmark dataset comprises 32,907 instances, with 15 real-integer attributes determining particulate matter 2.5 concentration. These attributes include year, month, day, hour, temperature, pressure, dew point temperature, precipitation, wind direction, wind speed, particulate matter 10 concentration, sulfur dioxide concentration, nitrogen dioxide concentration, carbon monoxide concentration, and ozone. The combination of these factors determines whether the air quality is healthy or unhealthy, with class rates of 62.42 % and 37.58 %, respectively.

As evident, these datasets differ in terms of data characteristics, including sample size, the type and number of attributes, and class balance rate. For instance, the sample sizes range from 244 samples in the "Algerian Forest Fires" dataset in the "Forest fire" category to 41,757 samples in the "Beijing Multi-Site Air-Quality Data" dataset in the "Air quality/pollutants concentration" category. Furthermore, they comprise 5 to 27 attributes with various data types, including Real and Real-Integer. The "Forest type mapping" dataset from the "Forest cover" category has the maximum number of attributes. The distribution of the number and types of attributes, as well as the imbalance rate of aforementioned datasets, is separately illustrated in parts ***(a)–(c)*** of Fig. (3), respectively. Concerning the number of attributes, the frequencies are 30 %, 50 %, and 20 % for "Lower than 10", "Between 10 and 20", and "More than 20", respectively. Attribute types are divided into "Real" and "Real-Integer", with frequencies of 70 % and 30 % respectively. Moreover, the imbalance rates are categorized into "Lower than 1.5", "Between 1.5 and 3", and "More than 3", with frequencies of 40 %, 40 %, and 20 % respectively.

Additionally, the classification rate has been employed as a metric to evaluate and compare the performance of the RJMLP against other intelligent models, the formulation of which is provided in Eq. (9). Moreover, the improvement achieved by the proposed classifier compared to baseline classifiers is calculated based on Eq. (10) [59].

$$Classification\ Rate = \frac{True\ Negative + True\ Positive}{False\ Positive + True\ Positive + False\ Negative + True\ Negative} \tag{9}$$

"True Negative" (TN) represents correctly identified negative data, "True Positive" (TP) denotes accurately classified positive data, "False Negative" (FN) refers to positive data wrongly classified as negative, and "False Positive" (FP) signifies negative data erroneously classified as positive.

$$Improvement = \frac{Classification\ Rate\ of\ proposed\ classifier -\ Classification\ Rate\ of\ baseline\ classifier}{Classification\ Rate\ of\ baseline\ classifier} \tag{10}$$

4. . Empirical results

The section is organized so that initially, the procedure for obtaining results, performances, and the improvement achieved by RJMLP for each dataset is thoroughly described using the "Algerian Forest Fires" benchmark dataset as an exemplary case. On this basis, an extensive evaluation of the RJMLP's performance compared to commonly used statistical/intelligent, shallow/deep, and single/hybrid classifiers is conducted using the "Algerian Forest Fires" dataset. Subsequently, to mitigate the potential influence of data characteristics on the RJMLP classifier's performance, the efficiency of the proposed RJMLP is assessed against commonly used statistical and shallow intelligent classifiers such as LR, MLP, and SVM. This assessment is performed using all 10 benchmark datasets from various domains, including air quality monitoring, temperature forecasting, forest ecosystem analysis, forest fire detection, and vegetation classification.

In this way, this section begins with a comprehensive analysis of a specific dataset, namely the "Algerian Forest Fires". This dataset comprises 244 instances and 7 attributes. The statistical characteristics of this dataset are detailed in Table 4. Furthermore, to enhance the visual comprehension of this benchmark dataset, pair plots of attributes and a distribution plot of classes have been visualized in Fig. (4) and Fig. (5), respectively. As observed in Fig. (4), there is an almost perfect correlation between X_5 and X_6, X_5 and X_7, and X_6 and X_7, as the points form nearly perfect lines. However, there is very little correlation between X_3 and X_5, X_3 and X_6, and X_3 and X_7. Additionally, the diagonal represents the empirical densities of each variable by target classes. It is evident that in almost all density curves of the variables, there is no distinct vertical line that clearly separates each class. In other words, there is no point where the two densities completely diverge. Overall, this plot illustrates the complex pattern of the data. In this research, the data is randomly separated, with 75 % allocated to the training set, 10 % to the validation set, and 15 % to the test set. To mitigate the influence of data random selection, the classifier estimation procedure is iterated 100 times.

Table 5 presents the classification rates for the RJMLP and the conventional MLP classifiers, along with the percentage of improvement achieved by the proposed classifier compared to the conventional one in the case of the "Algerian Forest Fires" dataset. The numerical results for this dataset illustrate that the RJMLP classifier, utilizing reliable and jumping-based methodologies, achieves an outstanding classification rate of 98.03 %. In contrast, the traditional MLP classifier, employing the standard continuous cost function, achieves a lower classification rate of 78.38 %. Importantly, the proposed RJMLP classifier demonstrates a performance enhancement of 25.07 % compared to the traditional MLP model. Hence, it can be inferred that the utilization of the reliable jumping-based cost function, which facilitates a robust learning process and aligns better with the objective function of classification, proves to be more effective in training multilayer perceptrons.

For a more extensive assessment of the proposed RJMLP's performance, Table 6 includes the classification rates of various established and commonly used single and hybrid classifiers. These classifiers comprise DT, RF, SVM, LR, Generalized Logistic Regression (GLR), a series of hybrid MLP and SVM (MLP-SVM), parallel hybrid MLP and SVM (MLP/SVM), Particle Swarm Optimization-based Multilayer Perceptron (PSO-MLP), Kalman filter-based Multilayer Perceptron (KMLP), along with other prominent deep learning models like DMLP, CNN and LSTM. The main reason for selecting this collection of classifiers is to consider the different types/characteristics of classification models in order to increase the validity of comparative outcomes. As evident, these classifiers encompass nearly all types of existing classifiers in the literature, including statistical, shallow intelligent, and deep learning models.

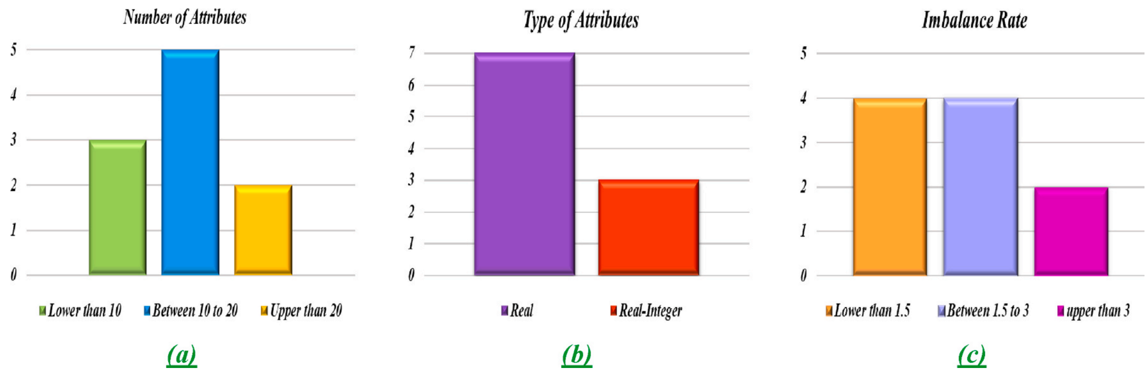

Fig. 3. Distribution of ***(a)*** number of attributes, ***(b)*** type of attributes, and ***(c)*** imbalance rate of the datasets.

Table 4
The characteristics of the "Algerian Forest Fires" dataset.

General information	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Minimum	22	21	6	0	0.70	6.90	1.10
Maximum	42	90	29	16.80	65.90	220.40	68.00
Mode	35	55	14	0	7.90	8	3
Median	32	63	15	0	11.30	33.10	12.25
Mean	32.17	61.94	15.50	0.76	14.67	49.43	16.66
Standard Deviation	3.63	14.88	2.81	2.00	12.37	47.67	14.20

Additionally, they cover both linear and nonlinear models, along with single and hybrid classification models. Furthermore, the selection includes various hybrid structures, incorporating preprocessing-based, parameter optimization-based, and component combination-based hybrid models, in both series and parallel forms.

The findings clearly demonstrate that the RJMLP approach excels in comparison to all other single/hybrid, statistical/intelligent, shallow/deep classification models. The empirical results indicate the most significant performance improvement, particularly when compared to LR, a single statistical classifier, with a substantial enhancement of 29.53 %. Indeed, this outcome is expected, as there is a common anticipation that a single intelligent classifier can outperform a single statistical model. Additionally, the proposed classifier exhibits a notable 28.28 % increase in the classification rate compared to GLR, a hybrid statistical model.

The second group of comparative classifiers includes single intelligent methods such as MLP, SVM, RF, and DT classifiers. The proposed model enhances the performance of these models by 25.07 %, 23.68 %, 21.88 %, and 24.36 %, respectively. These enhancements extend beyond single intelligent classifiers. Specifically, the proposed classifier boosts the classification rate by 22.91 %, 23.90 %, 24.80 %, and 23.40 % for the parallel hybridization of MLP and SVM (MLP/SVM), series hybridization of MLP and SVM

Fig. 4. Pair plots of the attributes based on their classes (Blue: 0, Red: 1).

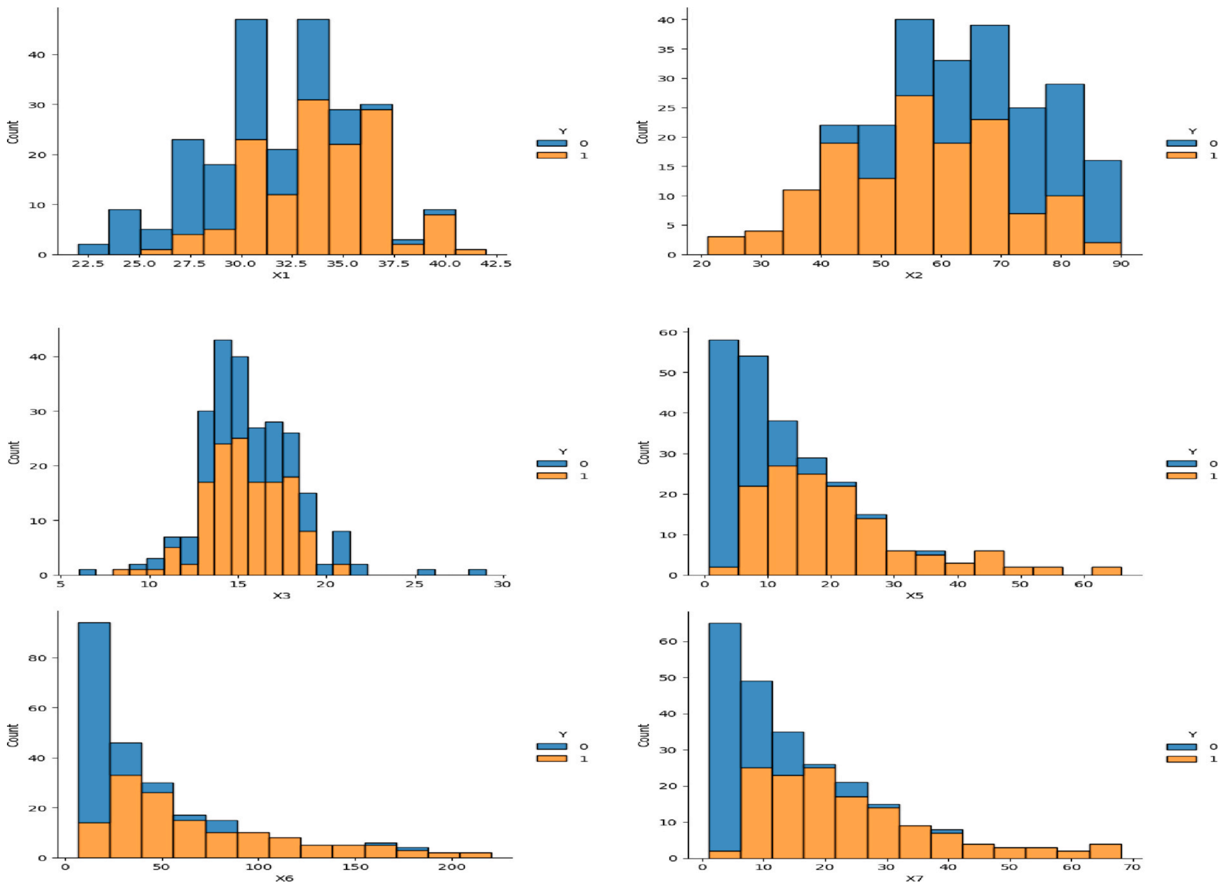

Fig. 5. Distribution plot of classes (Blue: 0, Red: 1).

Table 5
Performance comparison between the RJMLP and MLP classifiers for the "Algerian Forest Fires" dataset.

Data Set	Classification Rate		Improvement
	Proposed RJMLP	Classic MLP	
Algerian Forest Fires	98.03 %	78.38 %	**25.07 %**

Table 6
Comparison of RJMLP with other classifiers on the Algerian Forest Fires dataset.

Model	Type/Category	Performance (Accuracy)	Improvement
LR	Single/Statistical	75.68 %	**29.53 %**
GLR	Hybrid/Statistical	76.42 %	**28.28 %**
MLP	Single/Intelligent (Shallow)	78.38 %	**25.07 %**
DT	Single/Intelligent (Shallow)	78.83 %	**24.36 %**
SVM	Single/Intelligent (Shallow)	79.26 %	**23.68 %**
RF	Single/Intelligent (Shallow)	80.43 %	**21.88 %**
KMLP	Hybrid/Intelligent (Preprocessing)	79.44 %	**23.40 %**
PSO-MLP	Hybrid/Intelligent (Optimization)	78.55 %	**24.80 %**
MLP/SVM	Hybrid/Intelligent (Series Combination)	79.12 %	**23.90 %**
MLP-SVM	Hybrid/Intelligent (Parallel combination)	79.76 %	**22.91 %**
DMLP	Single/Intelligent (Deep)	88.64 %	**10.59 %**
LSTM	Single/Intelligent (Deep)	90.09 %	**8.81 %**
CNN	Single/Intelligent (Deep)	92.50 %	**5.98 %**
RJMLP	**Single/Intelligent (Shallow)**	**98.03 %**	————

Table 7
Classification rates of the proposed classifier compared to statistical and shallow intelligent models (All datasets).

Data Sets		Classifiers					
	RJMLP	LR	Improve	MLP	Improve	SVM	Improve
Forest fires	83.78	38.96	115.04 %	47.61	75.97 %	44.87	86.72 %
SML 2010	96.41	91.14	5.78 %	93.27	3.37 %	94.30	2.24 %
Numerical prediction model temperature	92.80	81.74	13.53 %	86.84	6.86 %	86.29	7.54 %
$PM_{2.5}$ of Five Chinese Cities	85.27	60.76	40.34 %	71.51	19.24 %	73.02	16.78 %
Beijing $PM_{2.5}$ Data	82.22	61.97	32.68 %	73.07	12.52 %	72.81	12.92 %
Beijing Multi-Site Air-Quality Data	99.34	92.48	7.42 %	95.83	3.66 %	95.77	3.73 %
Occupancy Detection	100.00	98.39	1.64 %	98.39	1.64 %	98.63	1.39 %
Wilt	99.20	80.58	23.11 %	91.60	8.30 %	90.53	9.58 %
Forest type mapping	99.90	98.72	1.20 %	98.72	1.20 %	98.59	1.33 %
Algerian Forest Fires	98.03	75.68	29.53 %	78.38	25.07 %	79.26	23.68 %
Average (Total)	**93.70**	**78.04**	**20.06 %**	**83.52**	**12.18 %**	**83.41**	**12.33 %**

(MLP-SVM), parameter optimization-based hybrid model of MLP using PSO algorithm (PSO-MLP), and preprocessing-based hybrid model of MLP using the Kalman filter (KMLP), all falling under the category of hybrid intelligent classification models. The last group for comparison involves deep intelligent models. The proposed RJMLP not only improves the classification accuracy of its conventional MLP and other shallow intelligent classifiers but also demonstrates the capability to enhance the performance of DMLP, CNN, and LSTM by 10.59 %, 5.98 %, and 8.81 %, respectively.

Ultimately, to mitigate the potential influence of data characteristics on the RJMLP classifier's performance, the model is assessed using the 9 remaining benchmark datasets. Table 7 presents the classification rates and improvements achieved by the proposed RJMLP compared to traditional LR, MLP, and SVM models. According to the empirical findings, it is apparent that across all 10 benchmark datasets, the RJMLP classifier significantly improves the classification rate compared to the conventional LR, MLP, and SVM models. On average, RJMLP outperforms LR by 20.06 %, with the degree of enhancement ranging from 1.20 % to 115.04 % across all 10 case studies. In a separate examination, the RJMLP demonstrates its superiority over MLP and SVM classifiers, resulting in an average improvement of 12.18 % and 12.33 % across all 10 benchmark datasets. However, the extent of improvement realized by the RJMLP model depends on the data's characteristics. Consequently, when we evaluate the performance of the proposed classifier compared to each conventional MLP and SVM classifier individually across all 10 benchmark datasets, the RJMLP consistently shows a range of enhancements, specifically from 1.20 % to 75.97 % compared to MLP and 1.33 %–86.72 % compared to SVM.

The numerical findings underscore the impact of data characteristics on the extent of enhancement. Depending on the specific dataset being analyzed, RJMLP's performance improvement compared to shallow intelligent models varied, ranging from 1.26 % for the "Forest type mapping" dataset to 81.19 % for the "Forest fires" dataset. Therefore, the results of this research validate the efficacy of incorporating the proposed reliable jumping cost function into the intelligent classifier's learning process and the estimation of unknown parameters. This approach leverages the benefits of both reliability and jumping strategies, resulting in the achievement of reliable and highly accurate results through a robust cost function that better conforms to the discrete nature of classification tasks.

5. . Discussions on results

The RJMLP classifier's capability to attain more accurate results can elevate the environmental significance of the model when compared to other classifiers. Typically, the most critical attributes influencing the environmental significance of a decision support system are accuracy and reliability. Enhancing accuracy leads to more precise environmental decision-making and policy formulation, while increasing reliability ensures decisions are made with greater confidence. Furthermore, there is no consensus in the literature regarding the superiority, significance, and relative impact of accuracy and reliability on decision quality [60]. Therefore, an ideal environmental decision support system must leverage both of these features to ensure qualified and profitable decisions. Given that the proposed RJMLP achieves both accuracy and reliability simultaneously, it can be regarded as a suitable alternative classifier for the environmental decision support system. Generally, the key findings and outcomes of the present study can be summarized as follows:

➢ This research introduces a novel cost/loss function for learning classification models through reliable and jumping methodologies.
➢ Based on empirical results, the RJMLP outperforms all single/hybrid statistical classifiers such as LR and GLR on average by an improvement of 28.90 %. Similarly, the RJMLP surpasses single shallow intelligent classifiers like MLP, SVM, DT, and RF, as well as hybrid shallow intelligent classifiers including KMLP, PSO-MLP, MLP/SVM, and MLP-SVM on average by an improvement of 23.74 %. Finally, the RJMLP demonstrates superior performance compared to deep learning classifiers such as DMLP, LSTM, and CNN, with an average improvement of 8.43 %. These results are based on the "Algerian forest fire" dataset.
➢ The results of the RJMLP model on all 10 benchmark datasets illustrate the superior performance of this classifier compared to statistical and shallow intelligent classifiers, including LR, MLP, and SVM, with an average improvement of 20.06 %, 12.18 %, and 12.33 %, respectively.
➢ The results support the hypothesis that utilizing a cost/loss function constructed based on reliable and jumping methodologies for classification problems may be more suitable and/or efficient.

➢ These findings underscore the significance of the cost function in achieving the desired accuracy, surpassing the influence of classifier structure and type. Therefore, a thoughtful selection of the appropriate cost function can substantially decrease modeling costs. Hence, the findings of this research validate the efficacy of incorporating the proposed reliable jumping cost function into the MLP classifier's training procedure and estimating unknown parameters.

In the end, the key advantages and limitations of the proposed RJMLP model are discussed. Typically, literature presents a range of aspects crucial for the practical evaluation and comparison of various modeling techniques. Key considerations, prioritized by importance, encompass accuracy, computational cost and time, interpretability, and ease of implementation. Numerical results demonstrate that the RJMLP surpasses traditional MLP and other single/hybrid statistical/intelligent classifiers in accuracy. Therefore, the significant advantage of this classifier, distinguishing it from other intelligent methods, is its accuracy. However, because of its discrete mathematical modeling, the RJMLP classifier requires more computational time compared to its traditional counterparts. Thus, the primary disadvantage of this classifier lies in its computational time. Moreover, akin to traditional MLP and other intelligent classifiers, the proposed model demonstrates poor interpretability. Hence, the RJMLP classifier's second disadvantage stems from its limited interpretability. Similarly, the process of designing and specifying the desired architecture of the proposed classifier, akin to traditional MLP and other intelligent models, poses challenges. Consequently, the third drawback lies in the complexity of utilizing and implementing the RJMLP classifier.

6. . Conclusion

The primary objective of this paper was to achieve remarkable accuracy by integrating the advantages of both jumping and reliability principles. This goal was accomplished by introducing a new cost function and guiding the learning process, leading to the establishment of a Reliable Jumping Classification Methodology. In this manner, the key accomplishments of the paper can be presented as follows:

(1) The proposed methodology designs robust jumping movements of estimated values during the learning process. This involves aligning the navigation method with the discrete nature of classification tasks and minimizing the variation of the mismatching function across different data situations, grounded in the concept of robustness.
(2) The proposed methodology combines the concepts of accuracy and reliability for the first time in designing a cost function for the classification model to achieve remarkable performance in various environmental application fields.
(3) This methodology has been applied to MLP, recognized as one of the most extensively utilized intelligent classification models, and proposes a novel MLP based on a reliable jumping cost function.
(4) The effectiveness of the proposed Reliable Jumping Multilayer Perceptron (RJMLP) classifier was confirmed using 10 environmental benchmark datasets chosen from various domains. These datasets encompass air quality monitoring, temperature forecasting, forest ecosystem analysis, forest fire detection, and vegetation classification.
(5) The empirical findings reveal that the proposed classifier outperforms the conventional versions of popular intelligent models, such as MLP and SVM, across all datasets. The performance evaluation demonstrates that the RJMLP classifier can improve the performance of the classic versions of MLP and SVM classifiers by 12.18 %, and 12.33 %, respectively.

As a result, this approach proves to be a viable and effective alternative to other shallow/deep intelligent methods in environmental applications, particularly when higher levels of accuracy and reliability are required. Accordingly, the proposed reliable jumping approach can be implemented across a range of classification models with distinct characteristics, serving as a supportive tool for environmental-related decision-making tasks such as climate change and drought prediction, monitoring air quality and pollutant emissions, specifying water and soil quality, and managing waste recycling, among others.

Additionally, the following recommendations for future work are suggested:

✓ Implementing the proposed reliable jumping approach on other types of classifiers, including statistical and shallow/deep intelligent classifiers, can be considered
✓ Assessing the efficiency of the proposed learning methodology in enhancing the classification rate across various categories of models would be valuable.
✓ Investigating the influence of classifier structure and data characteristics on the performance of the proposed classification methodology in comparison to other methods would provide valuable insights.
✓ Designing the suggested classification methodology for application in a hybrid structure of diverse classifiers would be a promising avenue for future research.
✓ Applying the proposed RJMLP classifier for decision-making in other scientific disciplines, such as medicine, finance, transportation, engineering, energy and renewable energy, and management, could yield valuable insights and contribute to advancements in various fields.

Data availability statement

Data used in the study is publicly available at the UCI website, and also is available from the corresponding author on reasonable request. Data will be made available on request.

Code availability

Code used in the study is available from the corresponding author on reasonable request.

Consent to participate

The authors declare that they consent to participate in this study.

Funding

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Consent for publication

The authors declare that they consent to the publication of this study.

CRediT authorship contribution statement

Sepideh Etemadi: Writing – original draft, Supervision, Software, Investigation. **Mehdi Khashei ,:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Ali Zeinal Hamadani:** Supervision. **Adeleh Kerdegari:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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