Assessing the Stability of a Multi-objective Heuristic Ensemble Classifier

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ABSTRACT. According to the random nature of heuristic methods, stability analysis of heuristic ensemble classifiers is essential. In this paper, for the first time, two-level factorial designs, as a statistical method, is used to perform stability analysis of a multi objective heuristic ensemble classifier which is designed by using Multi Objective Inclined Planes Optimization (MOIPO) algorithm as a new multi objective heuristic approach and the effects of two structural parameters of employed algorithm i.e. population size and number of iterations on the performance of designed ensemble classifier for two datasets, as representative of overlapped data and simple data, are investigated. Experimental results not only show the important structural parameters but also important interaction for each objective function. Finally, one can acquire regression model related to each objective function by using obtained results.

1. INTRODUCTION

An ensemble classifier incorporates a confined number of classifiers of same or different type, trained concurrently for a joint classification task [1]. The idea of ensemble learning is to learn a collection of classifiers instead of learning an individual classifier and then compound the outcomes of multiple classifiers [2].

In the process of designing an ensemble classifier, a variety of important issues exist so that each of them affects directly on the performance of the designed ensemble classifier. Among these topics, one can mention number and kind of base classifiers, method of training, method of making final decision and combining decisions, feature selection (possibly feature fusion) and even, the ultimate goal of designing an ensemble classifier. These problems inflict a complex search space with high dimensions on the researcher so it is often impossible to find the best solution in such space by using trial and error. On the other hand, heuristic approaches can acquire best solutions because of their capability of efficient probing in the solution space. Therefore, the utilization of these methods is proposed to design ensemble classifiers. Ensemble classifiers designed by heuristic algorithms are called heuristic ensemble classifiers.

It's worth noting that various responses can be received in different simulation runs due to the stochastic nature of heuristic methods. These responses are extremely associated with structural parameters of employed algorithms. Hence, the issue of stability in these

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algorithms has a special importance; stability of a heuristic algorithm means how much the changes of structural parameters influence the output of heuristic methods.

In this paper the stability analysis of a typical ensemble classifier is investigated by employing two-level factorial designs for the first time. In order to perform this, a multi-objective heuristic ensemble classifier is designed by using Multi-Objective Inclined Planes Optimization (MOIPO) algorithm at first and then the stability of this ensemble classifier is analyzed. In this step, the impact of two structural parameters on the designed ensemble is checked.

1.1 Two-Level Factorial Designs. Factorial designs are extensively employed in the experiments where it is essential to check the joint effects of multiple factors on a response variable. Joint factor effects signify main effects and interactions. A very important situation of the factorial design is where each of the k factors has only two levels. These designs are usually named 2^k factorial designs. It's worth mentioning that one of the applications of 2^k factorial designs is to adapt a first-order response surface model and to acquire the factor effect estimates.

The experimenter usually applies a factorial design to figure out the effect of two or more independent variables upon a single dependent variable. The simplest design, which is 2^2 factorial design, has only two factors, called A and B, each run at two levels.

Lowercase letters can also represent the four factor-level combinations in the design; the high level of each factor is specified by the corresponding lowercase letter and the low level of a factor is indicated by the lack of the corresponding letter. For example, a denotes the combination of factor levels with A at the high level and B at the low level [3].

1.2 Multi-Objective Inclined Planes Optimization (MOIPO) Algorithm. Heuristic algorithm is a method that ignores some of information to make decisions fast with maximum savings in time and with more precision than complex approaches [4]. This method applies a population to explore the problem space and thus guarantee greater probability to acquire optimal solutions [5].

IPO algorithm is inspired by the dynamic motion of spherical objects along frictionless inclined surface. These objects have tropism to attain the lowest points [6]. In this paper, multi-objective version of IPO is used.

2. MAIN RESULTS

The purpose of this paper is to accomplish stability analysis of a heuristic ensemble classifier by exerting two-level factorial designs which is not addressed in recent researches. So, at first, a multi-objective heuristic ensemble classifier with three objective functions is designed by employing MOIPO algorithm and then, the stability analysis of this ensemble classifier is performed by mentioned approach.

In the design step, the MOIPO algorithm is applied to find the best subset of classifiers in terms of ensemble size, error rate and diversity (diversity is described according to [7]) from an initial pool of classifiers.

Random subspace technique is used to construct the initial pool of classifiers and k-Nearest Neighbors (kNN) classifiers are selected as base classifiers. 10-fold cross-validation strategy is applied in the experiments.

Iris and Glass datasets are employed as a representative of simple data and overlapped data, respectively.

In stability analysis step, the impact of two structural parameters of applied heuristic algorithm on the designed ensemble classifier for each objective function is investigated. So, three points of Pareto front (ensemble with minimum size, ensemble with minimum error rate and ensemble with maximum diversity) are selected for response value. Also, considered parameters are population size and number of iterations and two levels for each parameter is assumed; 20 and 40 for population size and 100 and 200 for iterations.

Obtained data from two replicates for Glass and Iris are shown in Tables 1 and 2, respectively. Here, the effects of two factors i.e. Population size (A) and number of iterations (B) are studied.

Table1: Observed data for Glass

Treatment Combination	Replicate	Ensemble size	Error rate	*Q* statistic
1	I	4	0.0234	0.5731
	II	5	0.0187	0.5970
a	I	8	0.0421	0.6514
	II	11	0.0280	0.6282
b	I	7	0.0280	0.5512
	II	6	0.0234	0.5277
ab	I	6	0.0327	0.5824
	II	6	0.0327	0.5309

Table2: Observed data for Iris

Treatment Combination	Replicate	Ensemble size	Error rate	*Q* statistic
1	I	6	0.0667	0.6310
	II	6	0.0533	0.6539
a	I	10	0.0467	0.6724
	II	12	0.0600	0.7037
b	I	4	0.0667	0.6048
	II	6	0.0667	0.6497
ab	I	5	0.0600	0.6314
	II	7	0.0467	0.6425

Two standard error limits on the effects related to each objective function can be measured by using observed data. Equation (1) and (2) are the related intervals to Glass and Iris, respectively. According to above Equations, it's clear that both effects *A* and *B* in diversity measure, *A* in error and *A* and interaction *AB* in ensemble size are important effects for Glass because the related intervals do not include zero. Similarly, one can conclude that *B* in diversity measure and all effects (*A*, *B*, *AB*) in ensemble size are significant for Iris. Now, the regression model for each objective function can be specified; for example, when using Glass, the regression model for diversity measure is determined in Equation (3) in which x_1 and x_2 are the design factor *A* and *B*, respectively, on the coded (-1 , +1) scale and b_0 is the average of all 8 observations of diversity measure.

Another important point is the direction of each factor. For example, the main effect A for diversity measure is positive for Glass; this means that enhancing A from the low level to the high level will enhance the diversity measure. The main effect B is negative; this means that that enhancing B from the low level to the high level will decrease the diversity measure. Similar results can be obtained for other objective functions.

$$\begin{aligned}
&\textit{ensemble size}: && A: 2.2500 \pm 1.6583\\
& && B: -0.7500 \pm 1.6583\\
& && AB: -2.7500 \pm 1.6583\\
&\textit{error rate}: && A: 0.0105 \pm 0.0078\\
& && B: 0.0012 \pm 0.0078\\
& && AB: -0.0035 \pm 0.0078\\
&Q \textit{ statistic}: && A: 0.0360 \pm 0.0328\\
& && B: -0.0644 \pm 0.0328\\
& && AB: -0.0188 \pm 0.0328
\end{aligned} \tag{1}$$

$$\begin{aligned}
&\textit{ensemble size}: && A: 3 \pm 1.7321\\
& && B: -3 \pm 1.7321\\
& && AB: -2 \pm 1.7321\\
&\textit{error rate}: && A: -0.0100 \pm 0.0115\\
& && B: 0.0033 \pm 0.0115\\
& && AB: -0.0033 \pm 0.0115\\
&Q \textit{ statistic}: && A: 0.0276 \pm 0.0302\\
& && B: -0.0332 \pm 0.0302\\
& && AB: -0.0180 \pm 0.0302
\end{aligned} \tag{2}$$

$$\begin{aligned}
y &= b_0 + b_1 x_1 + b_2 x_2\\
&= 0.5802 + \left(\frac{0.0360}{2}\right)x_1 + \left(\frac{-0.0644}{2}\right)x_2
\end{aligned} \tag{3}$$

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