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A combined approach of base and meta learners for hybrid system

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Abstract

The ensemble learning method is considered a meaningful yet challenging task. To enhance the performance of binary classification and predictive analysis, this paper proposes an effective ensemble learning approach by applying multiple models to produce efficient and effective outcomes. In these experimental studies, three base learners, J48, Multilayer Perceptron (MP), and Support Vector Machine (SVM) are being utilized. Moreover, two meta-learners, Bagging and Rotation Forest are being used in this analysis. Firstly, to produce effective results and capture productive data, the base learner, the J48 decision tree is aggregated with the rotation forest. Secondly, machine learning and ensemble learning classification algorithms along with the five UCI Datasets are being applied to progress the robustness of the system. Whereas, the recommended mechanism is evaluated by implementing five performance standards concerning the accuracy, AUC (Area Under Curve), precision, recall and F-measure values. In this regard, extensive strategies and various approaches were being studied and applied to obtain improved results from the current literature; however, they were insufficient to provide successful results. We present experimental results which demonstrate the efficiency of our approach to well-known competitive approaches. This method can be applied to image identification and machine learning problems, such as binary classification.

1. Introduction

In the field of data mining, the classification task is to correctly predict the class of a given instance. Several theoretical and empirical studies have been published that demonstrate the advantages of the hybrid model. These approaches are known as multi-classifiers or ensembles. A huge number of research was carried out to produce multiple classifier systems based on the same classifier models trained on different data or feature subsets [1-2].

The primary agenda of the research is to evaluate and compare various techniques (J48, MP, SVM) with Bagging and Rotation Forest for binary classification. In this paper, we provide a technique based on the J48 Machine Learning algorithm integrated with the rotation forest ensemble learning algorithm [3-4].

Decision tree J48 is the execution of an algorithm (Iterative Dichotomiser 3). J48 algorithm is a classification algorithm producing a decision tree focused on information theory. It is one of the best machine learning algorithms for categorising and continuously examining data [5]. To produce accurate classification results, the J48 method is utilised to classify numerous applications.

On the other side, Rotation Forest is a method focused on feature extraction for generating classifier ensembles [6]. It has been broadly used to resolve a variety of tasks relating to medical images, computer vision and machine learning to achieve outstanding performances.

In [7], bagging and classification tree methods were combined to introduced the BAGCT and BAGCT-SVM framework to improve the reliability and robustness. The

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outcomes indicate that the BAGCT-SVM contributes improved analytical capability than CT and SVM.

This paper has been structured with several sections. Section 2, discusses the related works about machine learning and ensemble learning algorithms, mainly focusing on J48 and Rotation Forest. Section 3, presents the proposed methodology in detail. Section 4, describes the datasets, experimental methods, and outcomes. Finally, the conclusion and future works are stated in Section 5.

2. Related work

In general, hybrid system base and meta-approaches can enhance the effects and integrate the dynamic approaches in the system. A surge of research efforts has been recently witnessed for the classifications based on J48, MP, SVM and Bagging along with Rotation Forest. In this paper, we have included the classification of datasets concerning the base learners and meta-learners.

We analyzed various research articles to find current state-of-the-art developments in the domain of the Hybrid System. A few of them are discussed as follows:

In [8], proposed a hybrid model for Parkinson's diagnosis using machine learning techniques. The hybrid model includes feature selection methods such as an extra tree and mutual information gain and three classifiers k-nearest-neighbors, random forest and naive bayes. The combination of random forest and the genetic algorithm was performed and 95.58% accuracy was achieved.

In [9], the model is suggested primarily to assist and optimize the movement patterns of aged people. A new classifier named Apriori based Probability Tree Classifier (APTC) is integrated into the bagged J48 machine learning algorithm to yield a better outcome.

In [10], multiple ensemble methods Random SubSpace, Rotation Forest, Bagging, MultiBoost, Dagging and AdaBoost with the base classifier of Multiple Perceptron Neural Networks. The execution of the base classifier of MLP significantly improved concerning AUC. The results of the review are indicated in the current research, and paradigms using machine learning ensemble frameworks have worked properly.

In [11], extreme learning machine (ELM) created hierarchical learning structure was proposed for MP. The architecture of ELM based on feature extraction and random has initialized hidden weights. This method had better learning efficiency than Deep learning. The proposed algorithm achieved better and faster convergence than the existing state-of-the-art hierarchical learning methods.

In [12], robust machine learning SVM-based algorithms has been suggested. It is based on the framework of the double duality strategy of the decision-making process to get the additional constraints for optimization variables incorporated of imprecise information.

In [13], a hybrid ensemble learning method bagging, boosting, random forest and rotation forest along with logistic regression with stacking classifiers were introduced, which resultant occupy more space and consume more time for computations.

In [14], a rotation forest algorithm created on heterogeneous classifiers ensemble is applied to classified the gene expression outline. The local optimum and overfitting were improved through heterogeneous rotation forests. It improves the high stability, classification accuracy and time efficiency.

In [15], proposed a collaborative approach of blockchain and metaheuristic-enabled genetic algorithms. Blockchain technology provides a secure communication channel between stakeholders where a metaheuristic-enabled genetic algorithm, process and analyze the forecast pricing from records by scheduling, managing and monitoring them in real-time from day-to-day agriculture production detail. This approach achieved 95.3% accuracy and maintains transparency, integrity, availability and secure operational control access.

In [16], propsed the state-of-the-art utilization of ML algorithm, which are C4.5 (J48), K-Nearest Neighbor (KNN), Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), and One Rule (OneR) along with the five UCI Datasets. A retrospective study that looked at different sizes of training and test sets had a significant impact on the sensitivity and specificity of the same algorithm. The collaborative nature of the proposed system is to improve the efficiency of binary classification.

In [17], rotation forest algorithms are proposed for gene appearance of data classification. Three types of classification named; misclassification, test and rejection cost were integrated into the framework to make it more reliable and efficient. The experimental results have shown that the overall classification accuracy was improved significantly.

In [18], proposed a Parkinson's diagnosis system by using an optimized version of the BAT algorithm. Only 23 features were selected from the UCI Parkinson's disease classification data set and directly feed into the 23 neurons in the input layer of the model. The 96.74% accuracy was achieved by the proposed method with a 3.27% loss.

In [19], address the state-of-the-art utilization of ML in computer vision and image processing. This survey will provide details about the type of tools and applications and datasets. Multiple techniques and various types of supervised and unsupervised ML algorithms, the overview of image processing and the results based on the impact; neural network-enabled models, limitations, tools and application of computer vision have been discussed.

In [20], the metaheuristic optimization procedure along with the whale optimization set of rules and rotation forest algorithm was applied for the selection of email features and categorising the emails as spam and non-spam. The results obtained showed that the suggested technique generated notable improvement as compared with some previous methods.

In [21], compared and investigated state-of-the-art ensemble techniques Bagging, AdaBoost and Rotation Forest with the base classifier of J48 for the susceptibility of the landslide. The performance was assessed through ROC, AUC and statistical indexes. The J48 with the Rotation Forest model presented the highest prediction capability followed by AdaBoost and Bagging respectively. Moreover, J48 with Rotation Forest has proved the best-enhanced approach and promising one for better accuracy.

In [22], SVM, Naïve Bayes, Logistic Regression and K-Nearest Neighbor classifier had been utilized for binary classification. In supervised ML algorithms, the robustness of the method is progressed accordingly.

In the literature, some features have a negative impact on classification algorithms. The primary goal of classification is to reliably predict the target class for each occurrence in the data. A classification algorithm coordinates between the values of the predictors and the values during the model build training process.

3. Methodology

This section provides an overview of the proposed method, which describes the pre-processing stage of data and classification algorithms.

3.1. Overview of the proposed system

An overview of the proposed framework is given in Fig. 1. This system is composed of many phases: datasets, base learners, meta-learners and comparative analysis of the results. In addition, method generalization efficiency, 10-fold cross-validation, is used for all learners and datasets of the classifier.

3.2. Data pre-processing

In this phase, the ranges of the values of the data in datasets may be high. In such a scenario, certain features can significantly or negatively affect algorithms for classification accuracy. Therefore, the data assessments are normalized to the [0,1] range using the min-max normalization technique [23-24]. For mapping a value, of a feature x_i from the range [min(x_i), max(x_i)] to a new range [$minx_{new}$, $maxx_{new}$], the normalized feature $\hat{x}_i$ is computed as Eq. 1.

$$\hat{x}_i = \frac{x_i - \min_{x_i}}{\max_{x_i} - \min_{x_i}}(\max x_{new} - \min x_{new}) + \min x_{new} \quad (1)$$

3.3. Classification of algorithms

In this study, three base learners, including J48, MP, SVM and two Meta-Learners Rotation Forest and Bagging are employed as shown in Figure 1.

There are numerous phases of methods related to the datasets and classifiers. In this work, base learners and meta-learner along with several datasets, are experienced for binary classification.

4. Experimental work

In these subsections, we define and present the experimental procedure, measurements of evaluation and results of the experiment.

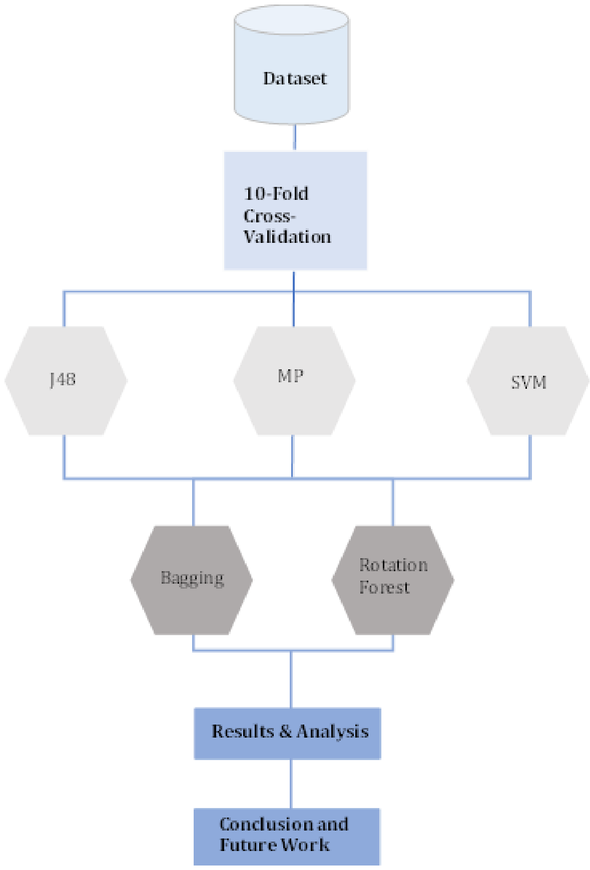

Figure 1. The framework of the method

4.1. Experimental process

In the experimental process, five datasets have been used from the UCI ML Repository [25].

All experiments are performed on base and meta-learners by using WEKA (Waikato Environment for Knowledge Analysis) ML toolkit and JAVA programming language [24]. We have utilized default parameter values for all the classifiers in WEKA.

On the other hand, we have carried out 10-fold cross-validation to all datasets to yield reliable results. The cross-validation is imposed on the original dataset randomly partitioned into 10 equally sized sets, one of which is used as test validation, while the remaining sets are used for training operations. The method is recurring 10 times and calculates the averages of the results.

Dataset characteristics are evaluated concerning the attributes and the number of instances. There are various numerical attribute descriptions illustrated in Table I. The number of instances, attributes, and classes for each dataset are presented in Table I. It is determined by investigating the appropriate data or datasets which are being utilized for binary classification problems.

Table 1. This is the example of table formatting

Datasets	Instances	Attributes	Classes
Abalone	4177	8	29
Balance Scale	625	4	3
Diabetes	768	8	2
German Credit	1000	21	2
Sonar	208	60	2

In this work, various approaches have been carried out along with several datasets, which are considered suitable for the classification. However, the performance metrics are calculated according to the binary classification problems based on the confusion matrix.

4.2. Assessment of measures

This section explains the proposed method's five performance assessment metrics, consisting of accuracy, AUC, precision, recall, and F-measure.

Accuracy reflects how close an agreed number is to a measurement. It is specified further in Eq. (2).

$$\text{Acc} = \left(\frac{TP+TN}{TP + FP+FN+TN}\right) \quad (2)$$

In equation 2, TN, FN, FP and TP show the number of True Negatives, False Negatives, False Positives and True Positives [13,16].

AUC represents the area under the ROC Curve. AUC calculates the whole two-dimensional area beneath the whole ROC curve from (0,0) to (1,1).

Precision is a positive analytical value [22,24]. Precision defines how reliable measurements are, although they are farther from the accepted value.

The equation of precision is shown in Eq. (3).

$$\text{Precision} = \left(\frac{TP}{TP+FP}\right) \quad (3)$$

The recall is the hit rate [13,16,22,24]. The recall is the reverse of precision; it calculates false negatives against true positives. The equation is illustrated in Eq (4).

$$\text{Recall} \quad \left(\frac{TP}{TP+FN}\right) \quad (4)$$

F-measure can be defined as the weighted average [13,16,22,24], of precision and recall. This rating considers both false positives and false negatives. The equation is illustrated in Eq (5).

$$F = 2\,x\,\frac{Precision\ *\ Recall}{Precision +\ Recall} \quad (5)$$

These criteria are adjusted proportionally in the data by the reference class prevalence in the weighting operation.

4.3. Experimental results

Table 2 presents classification accuracies for all datasets, base and ensemble learners. As it can be observed from Table 2, Rotation Forest with J48 gives highly accurate results than other approaches. In addition to the fact that meta learner bagging produces more accurate results than J48, MP and SVM base learners.

In Table 3, weighted precision values obtained by all base and ensemble classifiers for all datasets are presented.

In Table 4 and 5, weighted recall and weighted F-measure values are illustrated for all datasets, base and ensemble classifiers, respectively.

In Table 6, weighted AUC values are introduced for all datasets, base and ensemble classifiers. According to Table VI, Rotation Forest gives the best results very close or equal to 1.0. So, Rotation Forest can be determined to be a very powerful and effective classifier.

The balance scale, sonar and diabetes datasets have significant outputs concerning the accuracy, precision, recall, F-measure and AUC parameters; however German Credit has somehow satisfactory output and Abalone shows lower outcomes in Table 2-6.

Furthermore, it is analyzed that the Meta learner's rotation forest provides a more accurate outcome. Likewise, Meta learners bagging indicates adequate consequences. In addition, base learners provide positive findings.

Similarly, Figure 2-6, indicates the accuracy, AUC, precision, recall and F-measures values accordingly.

Table 2. Classification accuracies (%) For Uci datasets

	Base Learner			**Meta Learner Bagging**			**Meta Learner Rotation Forest**		
Datasets	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**
Abalone	21.12	26.24	24.11	23.10	**27.15**	23.63	**24.61**	27.00	**27.48**
Balance Scale	76.64	90.72	89.76	84	92.48	90.08	**90.72**	**94.24**	**90.40**
Diabetes	73.82	75.39	65.10	74.61	**76.82**	65.10	**76.30**	76.30	**76.30**
German Credit	70.50	71.50	68.70	73.30	**76.10**	68.60	**74.80**	75.40	**76.70**
Sonar	71.15	82.21	65.87	77.88	**83.65**	62.98	**79.81**	80.77	**85.10**

Table 3. Weighted precision values for Uci datasets

	Base Learner			**Meta Learner Bagging**			**Meta Learner Rotation Forest**		
Datasets	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**
Abalone	**0.36**	**0.43**	0.23	0.17	0.37	0.17	0.30	0.40	**0.43**
Balance Scale	0.73	0.92	0.83	0.81	0.92	0.86	**0.89**	**0.94**	**0.83**
Diabetes	0.73	0.75	0.65	0.74	**0.76**	0.65	**0.76**	**0.76**	**0.76**
German Credit	0.69	0.71	0.49	0.72	**0.75**	0.52	**0.73**	0.75	**0.76**
Sonar	0.71	0.82	0.72	0.78	**0.84**	0.66	**0.80**	0.81	**0.85**

Table 4. Weighted Recall Values For Uci Dataset

	Base Learner			Meta Learner Bagging			Meta Learner Rotation Forest		
Datasets	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**
Abalone	0.21	0.26	0.24	0.23	**0.27**	0.24	**0.25**	**0.27**	**0.27**
Balance Scale	0.77	0.91	0.89	0.84	0.92	0.90	**0.91**	**0.94**	**0.90**
Diabetes	0.74	0.75	0.65	0.75	**0.77**	0.65	**0.76**	0.76	**0.76**
German Credit	0.70	0.71	0.69	0.73	**0.76**	0.69	**0.75**	0.75	**0.77**
Sonar	0.71	0.82	0.66	0.78	**0.84**	0.63	**0.79**	0.81	**0.85**

Table 5. Weighted F-Measure Values For Uci Datasets

	Base Learner			Meta Learner Bagging			Meta Learner Rotation Forest		
Datasets	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**
Abalone	**0.40**	**0.47**	0.10	0.15	0.38	0.03	0.24	0.41	**0.39**
Balance Scale	0.75	0.91	0.86	0.82	0.92	**0.87**	**0.89**	**0.93**	**0.87**
Diabetes	0.74	0.75	**0.79**	0.74	**0.76**	**0.79**	**0.75**	**0.76**	0.75
German Credit	0.69	0.71	0.57	0.72	**0.75**	0.57	**0.74**	0.75	**0.74**
Sonar	0.71	0.82	0.62	0.78	**0.84**	0.59	**0.79**	0.81	**0.85**

Table 6. Weighted Auc values for Uci datasets

	Base Learner			Meta Learner Bagging			Meta Learner Rotation Forest		
Datasets	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**	**J48**	**MP**	**SVM**
Abalone	0.59	0.77	0.56	0.70	0.77	**0.59**	**0.72**	**0.78**	0.58
Balance Scale	0.81	0.98	0.91	0.93	**0.99**	0.96	**0.99**	**0.99**	0.94
Diabetes	0.75	0.79	0.50	0.79	**0.82**	0.50	**0.82**	**0.82**	**0.73**
German Credit	0.64	0.73	0.49	0.75	**0.78**	0.49	**0.78**	0.39	**0.69**
Sonar	0.74	0.88	0.64	0.89	**0.91**	0.70	**0.90**	0.89	**0.88**

- High Acc, AUC, Precision, Recall and F- measure is shown in Bold.

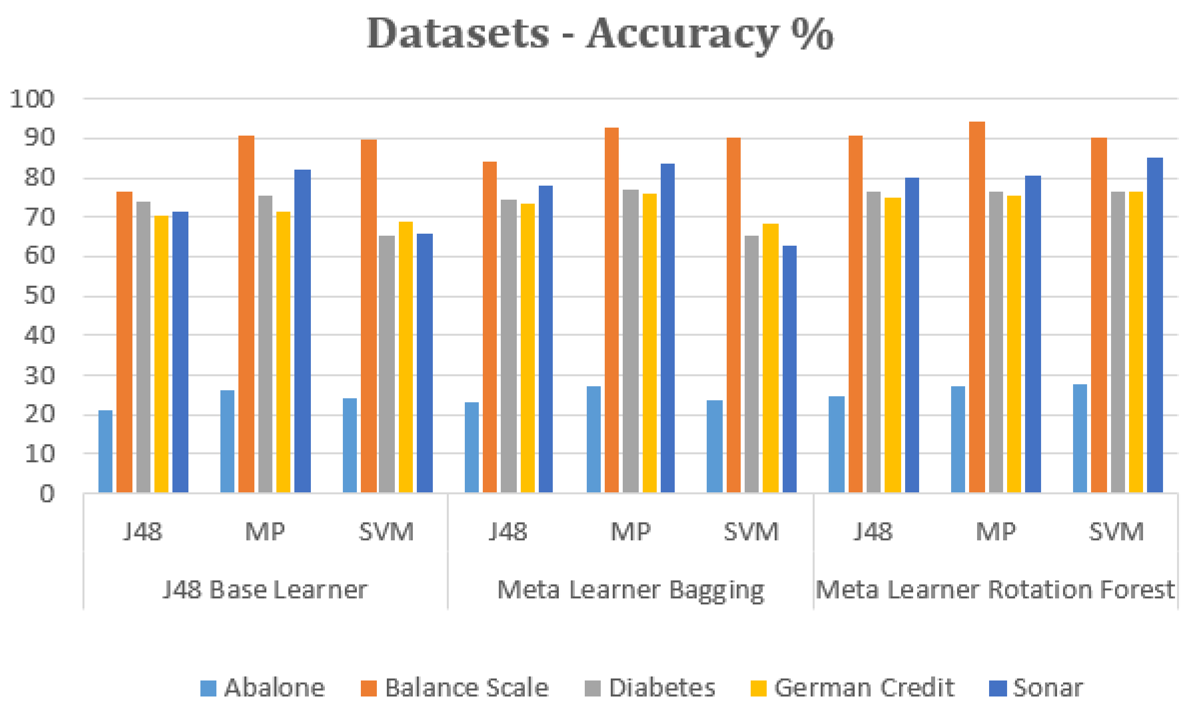

Figure 2. The chart showing the effects between datasets and accuracies

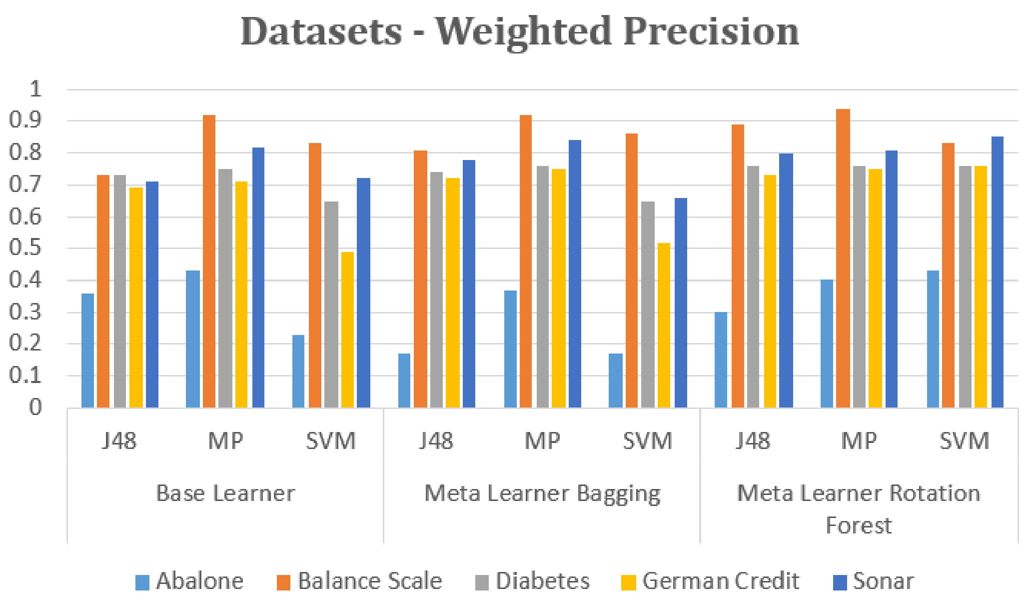

Figure 3. The chart showing the effects between datasets and weighted precision values

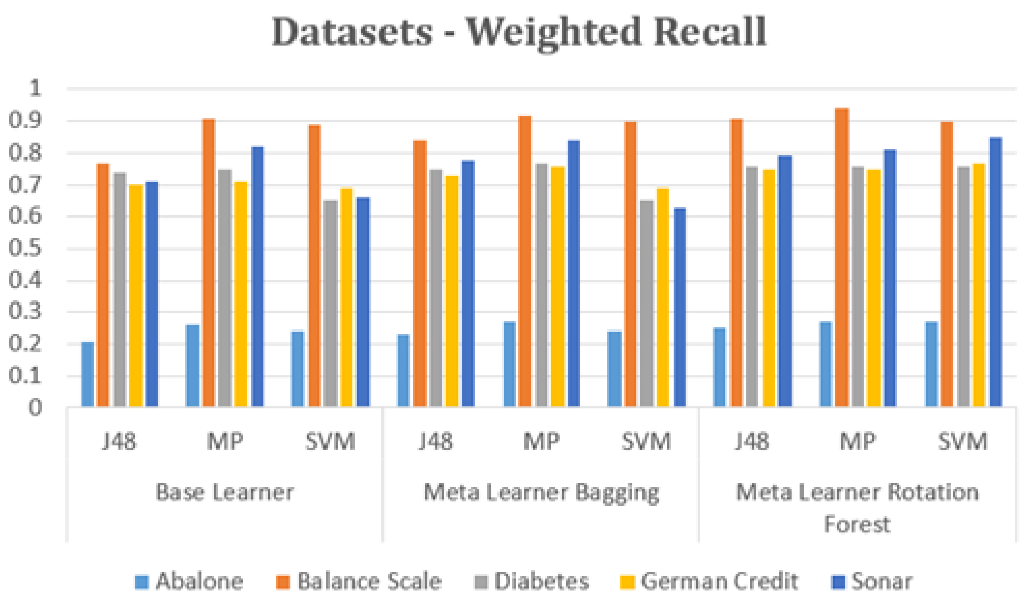

Figure 4. The chart showing the effects between datasets and weighted recall values

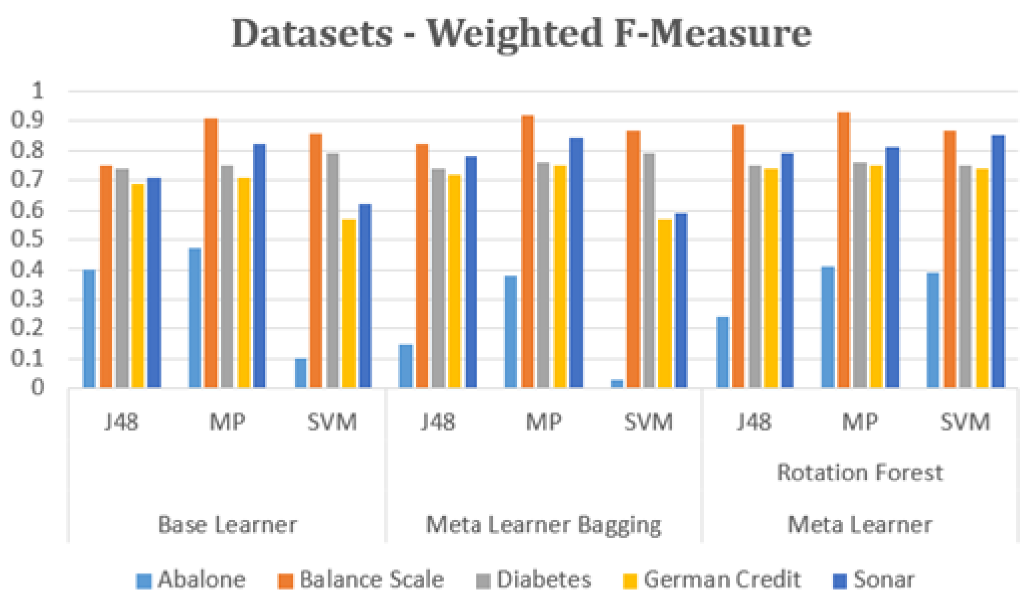

Figure 5. The chart showing the effects between datasets and weighted F-measure

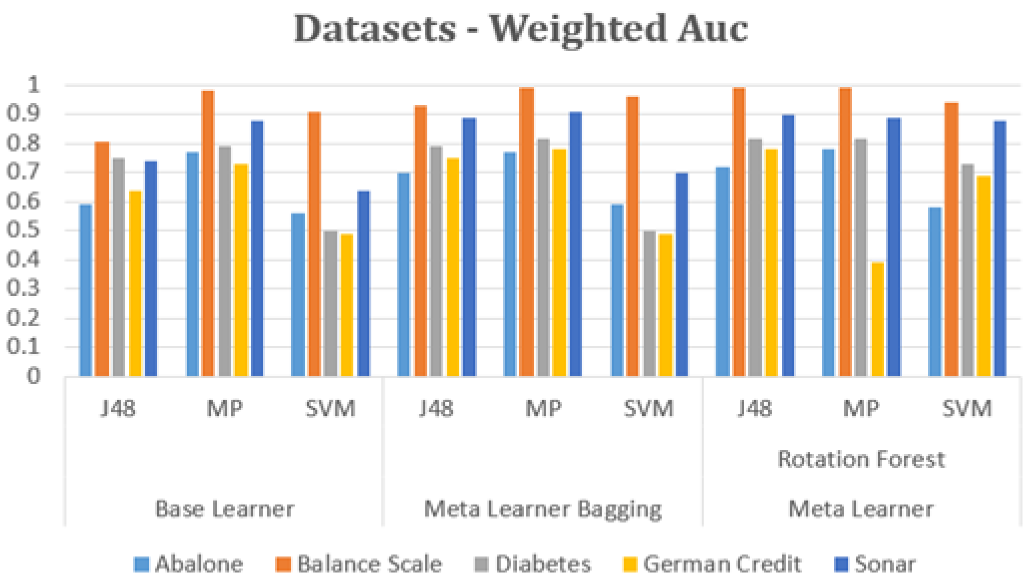

Figure 6. The chart showing the effects between datasets and weighted AUC values

5. Conclusions and future work

This section discusses Base and Meta Learners outcomes and future challenges in the existing Hybrid system. We investigated the various kinds of solutions to relevant problems and analyzed different types of approaches, tools, and techniques, but we couldn't find a single one that could do the entire task at once. Thus, the collaborative approach was proposed to analyze the Hybrid system. This collaborative nature of the proposed system is dependent on two different folds, such as the Base and Meta learner's approach. For the process of data collection, multivariate, categorical, integer and efficient records have been utilized for the Hybrid system. For finding the best results one has to try different methods. We have tried different methods and found the best combination. The results suggest that the use of the feature selection method is advantageous because it reduces complexity and increases accuracy. The performance of J48, MP and SVM with Rotation Forest has been studied using 05 datasets. The main objectives, priority of this proposed system and the key findings of this research work can be summarized as follows, based on the experimental and numerical results:

The Rotation Forest meta-ensemble learning method based on J48 is proposed in this paper. Although Rotation Forest can take more space and consume more time for computations, this method yields more efficient results by using hybrid advantages of base learners' algorithms.

The integration of other hybridization ensemble learning algorithms/approaches and deployment of emerging challenges is the primary focus of our future research.

Author contributions

Abdul Ahad Abro: Original draft and preparation; **Waqas Ahmed Siddique, Mir Sajjad Hussain Talpur, Awais Khan Jumani and Erkan Yaşar:** Reviewed, rewrote, performed part of the literature survey, edited, investigated and designed the architecture and explored software tools.

Conflicts of interest

The authors declare no conflicts of interest.

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