Ensemble Learning Gradient Boosting in Improving Classification and Prediction in Machine Learning

Bambang Siswoyo[a], Nanna Suryana[b], Zuraida Abas C[c], Deshinta Arrova Dewi D [d]

[a] Computer Fakulty, Masoem University (MU), Idonesia,
[b]Universiti Teknikal Malaysia Melaka (UTeM)
[c]Universiti Teknikal Malaysia Melaka (UTeM)
[d] INTI International University, Nilai Malaysia
Email: [a]bambangsiswoyo@masoemuniversity.ac.id and[d] deshinta.ad@newinti.edu.my

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Abstract: Ensemble methods have been studied extensively in machine learning. It is a meta-algorithms that combine several techniques in machine learning to create one predictive model. Ensemble Learning improves machine learning results by combining several models. This approach allows the production of better predictive performance compared to just a single model. Gradient Boosting is part of an ensemble technique that attempts to create a strong classifier from several weak classifiers. This paper focuses on three critical issues that need to be addressed in the boosting process. First is the classification techniques that are used; second is a combination method for conjoining several selected classifiers and last is the combined three classifiers. Afterward, a comparison study is conducted between the proposed Ensemble Learning Gradient Boosting (EL-GB) using three widely used classification techniques that consist of AdaBoost, Gradient Boosting, and XGB Classifier. Two financial ratio datasets of the banking industry have been employed in the experiments. The results show that the proposed EL-GB classifier has achieved a great performance with an accurate value of 98%. This performance is comparable with XGB Classifier that achieved 98% while AdaBoost is only 96%. In terms of data processing, the proposed EL-GB is easier to implement via matching process upon all available data, so the predict() function can be called to make predictions on the new data. It iteratively corrects weak classifiers. These results illustrate the capability of the proposed EL-GB to work on the banking industry data which can be used to detect a level of control in a bank while undertaking financial distress.

Keywords: Ensemble Learning, Boosting, Financial Ratio, Classification, Machine Learning

1. Introduction

Ensemble learning is a strategy where a group of models is used to solve problems that exist today, strategically ensemble learning combines various machine learning models into a single predictive model. In general, the ensemble method is mainly used to improve the accuracy of the overall performance of the model and combine some basic learners, for classification or prediction of the actual class. The more diverse the basic learner is, the stronger the final model will be. In each machine learning model, generalization error is given by the sum of the squares of bias + variance + irreducible error. By using the ensemble technique, it will reduce the bias and variance of the model. This reduces generalization errors overall.

Utilization of data in science applies to various fields to study hidden patterns and make predictions or descriptions accordingly, and it refers to the collection of techniques used to extract hidden knowledge, such as patterns, relationships, or rules from large data sets (Almasoud et al., 2015). This extracted knowledge can be analyzed and can predict future trends (Mhetre et al., 2017). Machine learning model optimization is an important step in producing more effective and efficient models. Optimization can include accelerating the database reading process, determining parameters for the hypothesis function.

Machine learning applications are found in the retail, banking, military, health, financial, image, housing, etc. sectors, to achieve their goals, researchers develop different algorithms using expertise from various fields of study (Cherfi at al., 2018; Berquist et al. , 2017; Tsai et al., 2014; Hsu at al., 2012; Jardin at al., 2018; Hung at al., 2006; Sun et al, 2017; Brahmana et al., 2005; Hemmatfar, 2018; Zi et al. ., 2016; Zhao et al., 2017; Khairalla at al., 2018; Priya et al, .2018; Janggo, 2018; Santosh et al, 2020; Pisula et al, 2020; Zi et al, 2016; Barboza at al. , 2017; Altman, 2000; David, 2011; Chen, at all, 2013). This algorithm can be used to build models, which can obtain insights from previous data. This can be applied to solve problems related to classification, regression, grouping, and optimization using algorithms such as decision trees, random forests, logistic regression, support vector machines (SVM), Naïve Bayes, K-Nearest Neighbor (KNN), K-Means, and others. Boosting also called "meta-algorithm" is a chronological or sequential process, in which each successive model tries to correct or correct previous model errors. Here, each successive model depends on the previous model [30]. The boosting model seeks to reduce model bias. Therefore, the boosting model unites several weak learners to form strong

learners. However, a single model may not achieve better accuracy than the entire dataset; performance is good for multiple fragments of the data set. Hence, each single model substantially improves (enhances) the performance of the ensemble. Some of the algorithms that generally improve are AdaBoost, GBM, XGBM, Light GBM and CatBoost.

In this paper, the proposed method is Ensemble Learning Gradient Boosting (EL-GB), whereby the EL-GB model has the advantage of being able to achieve a great prediction and classification performance. Generally, the EL-GB process using learning techniques that learns from previous mistakes rather than updates the weights of data points. Hence, it easier to implement compared than other algorithms

2.Methodology

The EL-GB model uses several base classifiers in the learning process and there are two stages identified in EL-GB learning. Stage 1 (training phase), each base classifier used is trained using the same dataset to produce the results of their respective predictions. Stage 2 (test phase), the Meta classifier takes the prediction results from the base class as input to determine which class is most likely to test data.

Hyperparameter optimization is the next stage to do by choosing a set of optimal hyper-parameters for a learning algorithm. In this study, it involves several decision trees used in EL-GB. Decision trees are added to the model sequentially in an attempt to refine and improve the predictions made by the previous trees. Thus, more trees are often better. The number of trees can be set via the n-estimators argument and the default is 100. The number of samples used for each tree can vary. This means that each tree fits into a randomly selected subset of the training data set. Using fewer samples introduces more variables for each tree, although it can improve the overall performance of the model. The number of samples used to match each tree is determined by the subsample argument and can be set to a fraction of the size of the training data set. This can be found in two machine prediction system models. The overall methodology diagram of the EL-GB method is depicted in Figure 1.

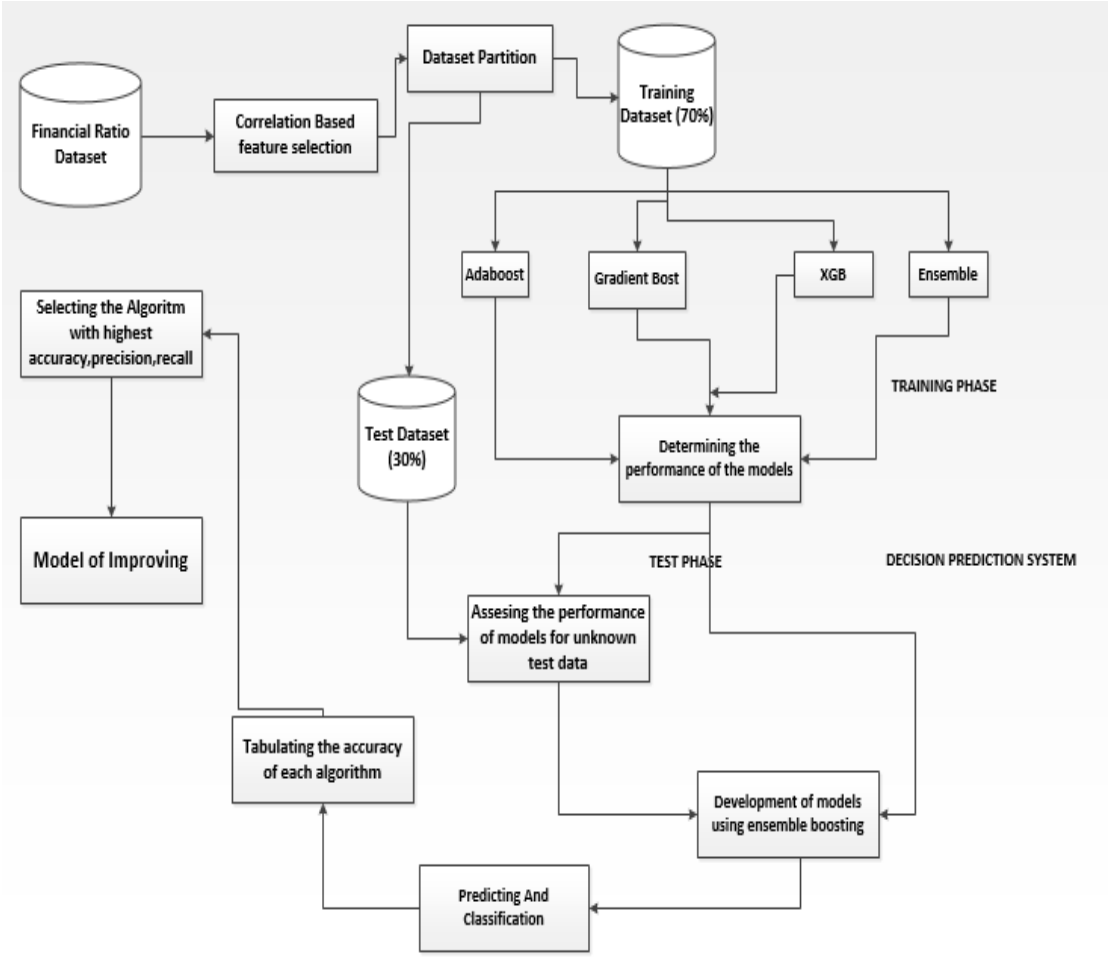


Figure 1. Ensemble Gradient Boosting Prediction

The study in this paper uses a dataset of banking industry financial ratios (bankruptcy dataset) that publish financial reports on the official web site (https://www.ojk.go.id) and the respective banking websites. The use of

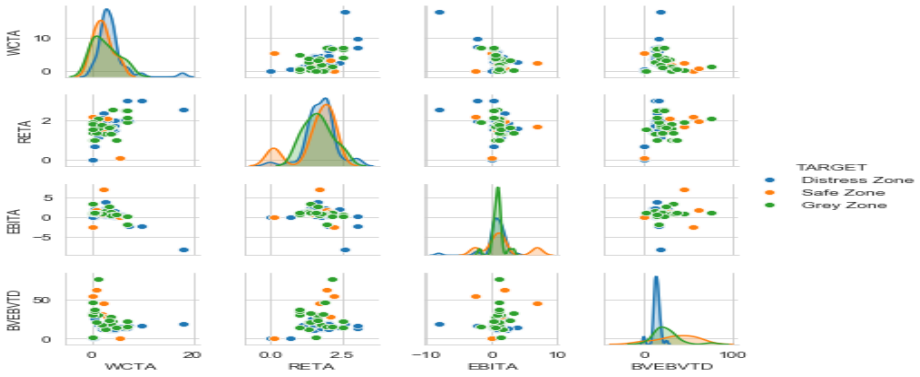
this primary dataset is intended for the classification of financial performance based on the Altman Z-Score. The features used are as follows: capital to total assets; retained earnings to total assets; earnings before interest and taxed to total assets; book value and book earning to total debt. While the output is Z-Score and target. The following is a summary of the financial ratio dataset used can be seen in Table 1 Financial Ratio Dataset. The method of measuring the results is used for measurement criteria, namely accuracy, precision, sensitivity, and specificity of testing 10 fold cross-validation

Table 1. Financial Ratio Dataset

WCTA	RETA	EBITA	BVEBDTA	ZSCORE	CLASS
4.2700	1.5000	0.6900	11.1000	0.4092	Distress Zone
.4376	0.1144	0.0610	0.2961	5.9081	Safe Zone
0.0024	0.0114	0.0177	0.0813	0.0852	Distress Zone
1.8000	1.5000	0.7200	31.4300	5.7425	Safe Zone
3.5900	1.6250	0.6100	27.6800	2.1127	Gray Zone
3.5200	1.8750	1.9000	13.1400	0.3796	Distress Zone
7.1000	1.9300	-1.8700	15.2700	1.2372	Distress Zone
1.8600	1.3000	1.3700	16.5400	0.0512	Distress Zone
6.8400	2.1200	0.1700	14.7600	1.1334	Gray Area
2.0900	1.7000	1.5000	11.5700	0.8147	Distress Area
0.1000	1.0000	0.8000	29.6000	1.2637	Gray Area
4.5700	2.0000	0.8800	11.9100	0.5932	Distress Zone
1.0200	1.3500	1.0300	20. 8300	1.7915	Gray Area
4.07000	2.000	0.27000	15.8500	0.6564	Distress Zone

Table 1 mainly captures parameters required by Z-Score. The parameters are WCTA (Ratio of Working Capital to Total Assets of the Firm), RETA (Ratio of Retained Earnings to Total Assets of the Firm) and EBITTA (Ratio of EBIT to Total Assets of the Firm). The financial ratio dataset shows that there are four features as independent variables and two features as target classes (distress area and gray area). The graph is shown in

Figure 2. Financial Ratio Dataset Graph



3.Results and Discussion

The results of the AdaBoost Based Classifier training dataset with n-estimator 5, Gradient Boosting with n-estimator 10, XGB with a max depth of 5, and a learning rate of 0.001, and ensemble using voting hard are shown in Table 2. Comparison Results of Distress Dataset Accuracy.

Table 2. Comparison Results of Distress Dataset Accuracy

Training Dataset	AdaBoost Classifier	Gradient Boost Classifier	XG Boost Classifier	EL-GB Classifier
	%	%	%	%
BankSaria	91	91	92	91
BankConven	96	98	98	98

Table 2 shows that the accuracy increases to 98% when using the boosting classifier based on the multiclass dataset. With majority voting, the AdaBoost model is 96%, although with other individual models the accuracy is just as good.

Table 3. Comparison Results of Confusion Matrix Accuracy

Training Dataset	Precision %	Recall %	F1-Score %
BankSaria	86	86	84
BankConven	86	86	84

Specific results may vary given the stochastic nature of the learning algorithm. In this case, we can see that the Boosting ensemble with hyperparameter the n estimator =10 achieves precision, recall, and F1-Score quite well on the four datasets as the ensemble boosting model can be used as the final model and make predictions for classification. First, EL-GB matches all available data, then the *predict ()* function can be called to make predictions on new data. A qualitative bankrupt dataset is a binary classification, the EL-GB model can evaluate on this dataset. The results of machine learning such as EL-GB show high potential for use in corporate bank distress finance prediction systems, especially when combined with knowledge of financial analysis. This paper strengthens research on the use of boosting that has been done by Santosh, (Santosh et al, 2020) with accuracy in ensemble boosting 98%. In this study, the level of accuracy with GradientBoost and XGBboost based learn shows the same accuracy with EL-GB, which is 98%. While AdaBoost is sensitive to noise data, this is greatly influenced by outliers because it tries to adjust each point perfectly so AdaBoost accuracy rate of 96%, lower compared to other based learn.

4.Conclusion

This study is designed to develop an Ensemble Learning Gradient Boosting (EL-GB), to be used over the bankruptcy dataset. The EL-GB can detect the level of control in the banking industry financial distress using a combination of based learning which refers to the performance of the model with the approach of three critical issues in boosting i.e. classification techniques, a combination method for combining several classifiers, and the number of classifiers to combine.

The proposed model, compared with other classifiers, significantly improves accuracy, recall, precision, and F1Score. The EL-GB is easy to implement, iteratively corrects weak classifier errors, and improves accuracy by combining weak based learns, can use many base classifiers, is not prone to overfitting.

In future research, various objectives can be considered as follows: Building a server that functions to store banking financial reports so that it can integrate data, expert knowledge, feature selection, balance operations on the dataset, and add the use of various other influencing factors as a level of distress control financial factors such as liquidity factors and corporate governance indicator factors to improve the detection performance of the level of financial distress control by learning ensemble boosting.

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