Ensemble learning: A review

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Abstract: : Clustering approaches in mathematical statistics and machine learning improve prediction performance by using multiple learning algorithms. Ensemble learning involves a modular collection of models, such as classification algorithms or experts, strategically coupled to tackle computational intelligence challenges Generally, ensemble learning is used to conduct and enhance the accuracy of models (classification, prediction, function approximation, and so on) or to limit the chance of unintentional bad selection. In addition to offering a level of confidence in the model's choice, selecting optimal (or near-optimal) features or qualities, data consolidation, incremental learning, non-static learning, and error correction are all uses of ensemble learning. This page explains ensemble learning, its several varieties, fields of application, studies and research that have employed this technology in learning, and the correctness of the results.

Keywords: Ensemble learning, boosting, Bagging, stacking.

1. Introduction

Often, evaluating an ensemble forecast requires more computation than evaluating just one model prediction. In some aspects, ensemble learning is considered a tool for compensating for poor learning algorithms by performing considerable extra effort. The alternative is to do far more instruction on just one non-ensemble system. If the same increase in computational, storage, or communication capabilities is applied to two or more procedures rather than a single method, an ensemble system may be more efficient in improving overall accuracy. Although fast algorithms (such as random forests) are commonly used in ensemble methods, slower methods may also benefit from ensemble approaches. Ensemble methods have also been employed in unsupervised learning contexts, such as consensus clustering and anomaly detection[1].

To improve the learning manage, develop powerful models, and discover the truth, it is necessary to aggregate all of these incomplete experiences using methods known as ensemble methods.

2. Ensemble learning

Methods of merging different learning algorithms in machine learning such that each algorithm assists its sister in order to increase the prediction process. The most well-known of these strategies is the subdivision of the model into groups, which is the tiny random forest, based on the basic idea that a set of weak decision classifiers reacts more strongly than a single big decision classifier. In summary, the ensemble learning procedure divides the artificial intelligence model into a set of tiny models throughout the learning phase and then converts it into a single powerful model before the prediction step. In this procedure, evaluation and voting mechanisms are used to eliminate models that degrade the prediction process (survival of the best or strongest)[2].

The Ensemble algorithm is a machine learning approach that is used to enhance the performance of statistics and predictive models. It is utilized in a variety of industries. This technique works on the premise of gathering several weak models (weak learners) and combining them to create a strong model that outperforms each of the models in the application.

3. Types of Ensemble Learning Methods

Below are the advanced types of ensemble learning methods[2][3] :

a) **Boosting**

Boosting is an ensemble strategy that improves future predictions by merging weak base learners into a strong learner. It involves gradient boosting, adaptive boosting, and XGBoost.

b) **Bagging**

Bagging, or bootstrap aggregation, is a technique used in classification and regression to improve model accuracy by using decision trees and reducing variance. It can be divided into two types: bootstrapping and aggregation. Bootstrapping collects samples from the complete population, while aggregation combines predicted outcomes and randomizes them.

c) **Stacking**

Stacking, or stacked generalization, is an ensemble approach that combines predictions from multiple learning algorithms for regression, density estimation, distance learning, and classification.

4. Basic Types of Ensemble Learning

Below are the basic Types of Ensemble Learning [4][5]:

- Averaging: Because it just averages all of the model predictions, this is the simplest ensemble approach to define. The average of the guesses is used to make the final prediction. This approach may be used to solve classification and regression difficulties.

- Max Voting Classifier: This approach is comparable to the average, except it excels in categorization tasks. Its reasoning is obvious. Several models provide forecasts known as "votes"; each prediction is worth one vote. Decisions are usually taken in favor of the vast majority of votes, as is generally the case with voting. The exact same thing is true in this case. The bulk of classifier predictions are used to get the final prediction.

- Weighted on average: A variant on the average method. In contrast to averaging, which gives the same weight to all mathematical models, a weighted average lends more weight to a model with stronger predictive power. Its relevance is expressed using weights. These weights are given as decimals that add up to one.

5. Boosting algorithm in Ensemble learning

Boosting is a machine learning algorithm in Ensemble Learning for automated categorization and prediction. It improves weak learners' performance by varying data weights, prioritizing incorrectly categorized data, resulting in improved model performance and accuracy.The following are studies in which boosting algorithm has been used in the ensemble learning in table (1).

Table 1. Summary of boosting research contributions to the ensemble learning.

Research name	Researcher	Year	The scale of using boosting algorithm	Results
[6]	Alafate ,J;...et al	2019	Research proposes alternative boost tree implementation for small memory size speedups.	Combining early stopping, effective sample size, and stratified sampling, this method accelerates training data by 10 to 100 over XGBoost.
[7]	Zhang ,Y;...et al	2020	Existing computational methods for discovering non-classical secreted proteins rely on simulated or limited datasets. Advancements in feature engineering, machine learning, and experimental validation offer new opportunities for developing improved predictors.	Researchers developed a two-layer Light Gradient Boosting Machine ensemble model for non-classical secreted proteins in Gram-positive bacteria, outperforming previous predictors. PeNGaRoo, an accessible online predictor, aims to expedite protein discovery and inspire future predictors.
[8]	Priya,S;...et al	2023	Data mining and machine learning methods aid in identifying cervical cancer causes. A multi-class classification approach using SVM and perception learning is implemented, addressing binary classification problems and using Gradient Boosting Machine (GBM) for improved accuracy.	Proposed model effectively identifies cervical cancer risk factors through accuracy and sensitivity evaluation.
[9]	Jin,W;...et al	2022	Novel RJSA for environment sound classification improves stability, robustness, accuracy, and generalization using energy, spectral entropy, ZCR, and MFCC features.	RJSA-based environmental sound classification algorithm improves accuracy by 14.6%.
[10]	Yang,S; ...et al	2017	GBDT is an ensemble learning method for short-term traffic	GBDT models improve prediction performance by combining traffic

			prediction using loop detector data. It trains simple decision trees with the error of the previous model, highlighting the interaction between input variables and response.	volume data from upstream and downstream detectors. The model's accuracy is generally higher than SVM and BPNN for different steps ahead, but multi-step-ahead models have lower accuracy. GBDT's prediction errors are smaller for 1-step-ahead models.
[11]	Mungoli,N; ...et al	2023	Researchers develop Adaptive Ensemble Learning framework for enhanced deep neural network performance by intelligently fusing features and enhancing model performance.	Adaptive Ensemble Learning framework improves deep learning performance by enhancing feature fusion, real-world scenarios, and adaptive ensemble models, training strategies, and meta-learning techniques.
[12]	Sibindi, R;...et al	2023	Study develops hybrid LGBM/XGBoost model to minimize variance, improve accuracy, and optimize hyperparameter combinations using bayesian hyperparameter optimization.	Hybrid model optimized regularization parameter values reduced variance, outperformed LGBM, XGBoost, Adaboost, and GBM algorithms in accurate house price predictions using MSE, MAE, and MAPE metrics.
[13]	Alzubi, J.A;...et al	2016	This paper proposes DivBoosting algorithm as an improvement to Boosting, focusing on misclassification errors and analyzing experiments on various datasets.	DivBoosting is a promising ensemble pruning method with advantages over traditional boosting due to its diverse classifier selection mechanism.
[14]	Fang, Z;...et al	2023	This work introduces gradient boosting (GB) as a training paradigm for physics-informed neural networks, enhancing performance by using a sequence of neural networks to solve challenging problems.	Numerical experiments show algorithm's effectiveness in comparisons with finite element methods and PINNs, enabling ensemble learning techniques.

6. Bagging algorithm in Ensemble learning

Bagging is an ensemble learning technique involving multiple models trained on different data subsets, reducing overfitting and improving model stability and accuracy. The following are studies in which bagging algorithm has been used in the ensemble learning in table (2).

Table 2. Summary of bagging research contributions to the ensemble learning.

Research name	Researcher	Year	The scale of using bagging algorithm	Results
[15]	Tuysuzoglu,G;...et al	2020	The paper introduces enhanced Bagging (eBagging), a modified bagging technique using error-based bootstrapping for training sets. It was tested on 33 benchmark datasets and compared to existing classification algorithms.	eBagging outperforms competitors by accurately classifying data points and reducing training error.
[16]	Kabari, L . J; ...et al	2019	On an iris dataset, we conducted a demonstration study of Bagging and Voting ensemble learning methods.	Bagging outperforms voting in ensemble learning based on experimental data.
[17]	Ngo, G; ...et al	2022	Paper proposes evolutionary bagged ensemble learning using algorithms to enhance ensembles by providing diversity.	Evolutionary ensemble bagging outperforms conventional methods for benchmark datasets, sustaining diverse bags without reducing performance accuracy.
[18]	Zareapoor, M;... et al	2015	Paper trains and evaluates data mining techniques for credit card fraud detection.	Introduced bagging classifier for fraud detection using decision three, evaluated on real-life credit card transactions dataset.
[19]	Frank, E; ...et al	2006	This paper explores sampling from kernel density estimator and data to create new training sets, controlling the amount of "smear" with a parameter.	Improved input smearing method improves classification and regression results compared to bagging.
[20]	Liu, X; et al	2019	This paper introduces the Gradient Boosting Decision Tree (GBDT) method to Bagging framework and proposes a prediction model called Bagging-GBDT. It predicts PM2.5 concentration in Beijing, China, and measures its validity using support vector machine regression and random forest models.	Bagging-GBDT model reduces bias, variance, and improves prediction effect compared to SVR and random forest.
[21]	Xu, S.B;...et al	2020	Study uses Bagging ensemble-learning algorithm for 1-6 hour Dst index prediction using solar wind parameters.	The Bagging ensemble model enhances point and interval prediction accuracy by reducing error and correlation coefficients, and achieving better stability and accuracy in predicting magnetic storm events.
[22]	Tüysüzoğlu, G;...et al	2022	T-Bagging is a new ensemble learning method that assigns larger weights to recent samples, reducing selection chances and adapting to dynamic system changes.	T-Bagging method enhances model prediction accuracy in temporal data experiments.

7. Stacking algorithm in Ensemble learning

Stacking is a machine learning technique that optimizes the performance of multiple models by training a single model with secondary training data. It is a sophisticated yet effective method for classification and prediction problems. The following are studies in which stacking algorithm has been used in the ensemble learning in table (3).

Table3. Summary of stacking research contributions to the ensemble learning.

Research name	Researcher	Year	The scale of using stacking algorithm	Results
[23]	Yao, J; ...et al	2022	Research evaluates flash flood potential in Jiangxi, China using ensemble learning and four base models.	The blending approach outperforms other models in evaluating flash flood vulnerability in Jiangxi catchments.Maps reveal 50% province vulnerable to flash floods. This helps develop disaster prevention plans and improve public awareness.
[24]	Chen, J; ... et al	2019	A stacking model using Himawari 8 satellite data estimates PM2.5 concentrations in Central and Eastern China.	The stacking model outperformed single models in accuracy evaluation, outperforming single models in North China Plain, China's most polluted area.
[25]	M. Jiang, M;...et al	2020	The paper presents a stacking framework for forecasting stock price index direction using deep learning algorithms and tree-based techniques, eliminating overfitting and revealing distinctive learning patterns.	Enhanced Stacking technique outperforms ensemble learning and deep learning in US stock indices, providing improved financial analysis.
[26]	Li ,G;...et al	2021	This paper proposes an enhanced Stacking sensor fault detection approach using fault-discrimination information, using ensemble learning models and evaluating detection performance using AUC and FPR.	IStacking improves ROC curve area and false positive rate by 2.85%.
[27]	Akyol,K;...et al	2020	Study compares stacking ensemble approach-based model for epileptic seizures using Bonn University clinical dataset.	The proposed stacking ensemble-based deep neural networks model outperforms base DNN model in epileptic seizure detection, with an average accuracy of 97.17% and sensitivity of 93.11%. This makes it suitable for expert systems and decision support systems, improving epilepsy clinical diagnosis and therapy.
[28]	Basith, S; ...et al	2022	The study introduces STALLION, a novel predictor for prokaryotic Lysine AcetyLatION, using six species-specific models to accurately identify Kace sites. 11 encodings were used to extract patterns, and a systematic feature selection approach was used to identify optimal features.	STALLION outperforms existing predictors in independent tests; user-friendly online predictor implemented.
[29]	Chao,L. I;...et al	2020	This work presents a star/galaxy classification system using stacking ensemble learning for accurate classification in Sloan Digital Sky Survey's darkest source magnitude collection. The algorithm compares outcomes with various models.	Stacking ensemble learning improves galaxy classification accuracy by 10% compared to function trees.
[30]	Yang,Y;...et al	2021	A two-layer stacking ensemble learning framework distinguishes	Stacking ensemble model improves Parkinson's disease

			early Parkinson's disease from healthy control using multimodal neuroimaging and early clinical evaluation, achieving 96.88% accuracy.	diagnosis and earlier identification using multiple classifiers.
[31]	Gu, L;...et al	2022	Ensemble learning model uses four machine learning models for forecasting climatic indices, atmospheric factors, and local meteorological data.	Taihu Basin's basic models showed better performance in spring and winter, with improved accuracy in rainy seasons using a stacking ensemble multi-ML framework.

8. Conclusion

Ensemble Learning is a useful approach for improving prediction accuracy and resilience by combining numerous models. It is especially beneficial when a single model is insufficient or dependable enough to produce accurate predictions. Ensemble Learning approaches including Bagging, Boosting, and Stacking have been shown to be useful in a variety of applications such as classification, regression, and clustering. However, finding the proper model combination and modifying the parameters may be a difficult undertaking that necessitates thorough analysis of the data and the situation at hand. Overall, Ensemble Learning is a useful technique for data scientists and machine learning practitioners trying to enhance model performance and produce more accurate predictions. For several reasons, an ensemble is preferable to a single model:

- **Performance:** Ensemble learning produces a powerful learner, as indicated in the prior section. The outcome of weak learners is the strong learner. As a result, the prediction powers of models improve. When compared to a single model, the performance is improved.
- **Error reduction:** Bias and variance can be used to explain machine learning model prediction mistakes. The disparity between a forecast and the actual outcome is characterized as bias. The sensitivity of a model to modest changes in the training set is characterized as its variance. It is preferred to have a model with minimal bias and variance, but this is challenging to obtain in practice.

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