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Hybrid Ensemble Learning and AHP for Housing Price Prediction

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Abstract

In this paper, a hybrid approach combining ensemble learning and the Analytic Hierarchy Process (AHP) is proposed for selecting the best model to predict housing prices. Initially, three base models—including Random Forest, AdaBoost, and XGBoost—were trained and optimized using GridSearchCV, and their performances were evaluated based on accuracy, training time, and interpretability criteria. Then, the weight of each criterion was systematically determined using AHP to incorporate the relative importance of the criteria in the model selection process. Finally, model weights were obtained based on the weighted scores from these criteria, and a Voting Regressor ensemble model was constructed using these weights. The results showed that although XGBoost achieved the highest accuracy, AdaBoost obtained a higher score within the AHP framework due to its shorter training time and better interpretability. This study demonstrates that the simultaneous use of ensemble learning and AHP can significantly aid in model selection in Machine Learning (ML), especially when multiple and conflicting criteria are involved.

Keywords: Ensemble learning, Model selection, Analytic hierarchy process, Housing price prediction.

1 | Introduction

Machine Learning (ML), a prominent branch of artificial intelligence, focuses on the development of algorithms and models capable of learning from data to make accurate predictions and informed decisions. By leveraging large volumes of historical data and diverse features, ML enables automated analysis and the extraction of latent patterns. This technology finds extensive applications across various domains such as economics, healthcare, marketing, and social sciences, playing a crucial role in digital transformation and data-driven decision-making. Continuous advancements in ML algorithms, coupled with increased computational power, have facilitated the emergence of sophisticated tools for prediction, classification, and optimization. However, one of the significant challenges in this field lies in selecting the most appropriate model based on

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data characteristics, prediction accuracy, training speed, and interpretability—factors that hold critical importance in real-world applications.

Ensemble learning represents an advanced approach within ML, wherein multiple base models are combined to enhance overall predictive performance. By aggregating the outputs of diverse models, ensemble methods effectively reduce individual model errors and yield more accurate and robust predictions. Prominent ensemble algorithms such as Random Forest, AdaBoost, and XGBoost have demonstrated widespread success across a range of prediction tasks, notably in housing price forecasting. Despite their advantages, selecting the optimal ensemble model is a complex process that extends beyond mere accuracy comparison. Practical criteria such as training time and model interpretability must also be considered, as they significantly influence model adoption and usability in real-world scenarios. This necessitates the employment of multi-criteria evaluation frameworks for balanced and intelligent model selection.

The Analytic Hierarchy Process (AHP) is among the most widely utilized and validated Multi-Criteria Decision-Making (MCDM) methods, which quantifies the relative importance of various criteria through pairwise comparisons. AHP enables decision-makers to systematically evaluate both quantitative and qualitative factors, deriving numerical weights that facilitate the integration of multiple criteria into a coherent selection process. When combined with ML techniques, particularly ensemble learning, AHP offers a comprehensive evaluation mechanism that accounts not only for prediction accuracy but also for computational efficiency and model interpretability. Such integration supports the selection of models that are both technically sound and practically applicable.

This study aims to propose an integrated framework for selecting the best housing price prediction model, wherein prediction accuracy, training time, and interpretability are weighted using AHP. Subsequently, these weights guide the combination of Random Forest, AdaBoost, and XGBoost ensemble models. This approach assists decision-makers in making informed, balanced, and practical choices by considering both technical performance and operational feasibility, ultimately contributing to more effective deployment of ML models in real-world applications.

With the rapid expansion of data generation and computational capabilities, ML has emerged as a transformative tool across various fields, including housing, economics, and public policy. ML algorithms can uncover complex, non-linear patterns from data and are particularly valuable for predicting housing prices based on socioeconomic and environmental indicators. In this context, ensemble learning models such as Random Forest, AdaBoost, and XGBoost have demonstrated robust predictive performance and are frequently implemented using the powerful Scikit-learn library in Python [1].

Complementing ML techniques, Data Envelopment Analysis (DEA) provides a non-parametric approach to evaluating the relative efficiency of Decision-Making Units (DMUs), including schools, bank branches, and contractors. DEA has been used extensively for performance evaluation in various sectors. For instance, Bagheri Toulabi et al. [2] employed DEA to rank students' mathematical abilities, while Asnaashari et al. [3] applied a grey DEA approach to contractor selection. Taghizade Tame et al. [4] proposed a DEA model for fixed-cost allocation in banking systems with undesirable outputs, and Keshtkar et al. [5] developed network DEA-R models for systems with both desirable and undesirable outputs.

Recent contributions have expanded DEA's theoretical foundation and applications. Gerami et al. [6] proposed a fully fuzzy slacks-based DEA model, while Lotfi et al. [7] introduced a slack-based evaluation model within DEA and DEA-R frameworks. Fallahnejad et al. [8], [9] developed modifications to the Malmquist productivity index by incorporating dual frontiers and Nash bargaining models to assess eco-innovation in the transport sector. Moreover, studies by Shahsavan et al. [10] and Mohammadi et al. [11] investigated DEA in contexts involving congestion and integer data clustering, respectively.

Structural and interpretive modeling approaches have also complemented DEA applications. For example, Khodadadi Karimvand et al. [12] identified aggregation factors in production planning through fuzzy interpretive structural modeling. In addition, Sohrabi et al. [13], [14] utilized DEA-R for strategic alliance modeling, further emphasizing DEA's versatility. Noura et al. [15] introduced a super-efficiency model accounting for societal effectiveness. These advances highlight DEA's adaptability in multi-input, multi-output settings, making it suitable for real estate assessment as well.

Significant advancements in DEA-R models have focused on cost and revenue efficiency, exploring the relationship between classic DEA models without explicit inputs and DEA-R models, as well as methods for identifying efficient frontiers within these frameworks. These contributions have enhanced both the theoretical foundation and practical application of DEA-R, facilitating more accurate efficiency evaluations and resource optimization in various industries [16]–[18].

Despite these advancements, selecting the optimal predictive model remains a multi-dimensional decision problem. In this context, AHP offers a structured approach to weighting diverse evaluation criteria such as accuracy, training time, and interpretability [19]. Integrating AHP with ensemble learning provides a practical decision-support framework. This study proposes a novel, unified approach that combines DEA for efficiency labeling, ensemble learning for predictive modeling, and AHP for multi-criteria evaluation, offering a balanced and interpretable solution to the challenge of housing price prediction. Fundamental concepts, including ML, ensemble learning, the AHP, and the scikit-learn library, are the primary tools for model implementation. Section 3 details the methodology, describing the preparation of the Boston Housing dataset and training of three powerful ensemble models—Random Forest, AdaBoost, and XGBoost—using hyperparameter optimization and data standardization. The models are evaluated based on accuracy, training time, and interpretability, with weights assigned through AHP to compute final scores for model selection.

Section 4 presents a case study on housing price prediction, where the models are trained and evaluated on the Boston dataset. Results are reported in tables showing optimized parameters, training durations, and model performances, with a multi-criteria comparison of the models. Section 5 discusses conclusions emphasizing the importance of integrating ML with AHP for effective and practical model selection in real-world problems and suggests directions for future research.

2 | Background

2.1 | Machine Learning

ML refers to a subset of artificial intelligence that enables systems to learn patterns from data and make predictions or decisions without being explicitly programmed. It has become an indispensable tool in many domains, including finance, healthcare, marketing, and urban planning. Supervised learning, one of the main branches of ML, is particularly relevant in regression and classification tasks where labeled data is used to train predictive models. ML models range from simple linear regressors to more complex algorithms like support vector machines, decision trees, and neural networks. The increasing availability of high-dimensional datasets has shifted the focus from merely building accurate models to also considering aspects such as scalability, interpretability, and training efficiency. These considerations are critical when selecting a suitable model for real-world applications.

2.2 | Ensemble Learning

Ensemble learning is a powerful ML paradigm that combines multiple base learners to form a more accurate and robust model. The main idea is that while individual learners may make errors, their combination—if properly designed—can outperform any single model. Ensemble methods are generally categorized into three main types: Bagging, boosting, and stacking. Bagging (e.g., Random Forest) reduces variance by training multiple models on different subsets of the data and averaging their predictions. Boosting (e.g., AdaBoost, XGBoost) sequentially trains models, focusing more on the instances misclassified by previous ones, aiming to reduce bias. Stacking combines several learners via a meta-learner that synthesizes their outputs for the final prediction. These techniques have demonstrated superior performance in various ML competitions and real-world problems, especially where the underlying data is complex and noisy.

2.3 | Analytic Hierarchy Process

The AHP, introduced by Saaty [20] in the 1970s, is a structured technique for organizing and analyzing complex decision-making problems. It allows decision-makers to model a problem in a hierarchical structure and compare the relative importance of different criteria using pairwise comparisons. These comparisons are then synthesized to produce weights that reflect the decision-maker's preferences. In the context of ML, AHP is particularly valuable for multi-criteria model evaluation, where trade-offs between conflicting metrics (e.g., accuracy vs. interpretability) must be balanced. By using AHP, subjective assessments of importance can be quantified, providing a rational foundation for selecting among alternative models based on multiple evaluation dimensions.

2.4 | Scikit-Learn

Scikit-learn is one of the most widely adopted open-source libraries for ML in Python, known for its clean syntax, reliability, and rich functionality. Built on top of core scientific Python packages such as NumPy, SciPy, and matplotlib, it provides a consistent and efficient interface for a broad range of ML tasks, including classification, regression, clustering, dimensionality reduction, and model selection. Its design promotes modularity and reusability, enabling both novice and experienced users to prototype and evaluate ML models rapidly.

Among its key features are potent tools for hyperparameter tuning such as GridSearchCV and RandomizedSearchCV, a flexible pipeline system for integrating preprocessing and modeling stages, and native implementations of popular ensemble learning algorithms such as Random Forest, AdaBoost, and Gradient Boosting. Due to its ease of use, extensive documentation, and active community support, scikit-learn is widely used in both academic research and industrial applications, making it a standard toolkit for data-driven experimentation and deployment. Due to its flexibility, simplicity, and extensive documentation, scikit-learn is highly suitable for rapid prototyping and educational use, as well as for deployment in professional data science projects.

3 | Methodology

This study utilizes the Boston Housing dataset, a widely recognized benchmark dataset in the field of ML, which consists of 506 samples and 14 variables encompassing various economic and geographic factors. The target variable is the Median Value of owner-occupied homes (MEDV), representing housing prices in thousands of dollars. The dataset was sourced from the original repository and loaded with a custom approach due to its specific formatting; alternating rows of data were combined to reconstruct the complete dataset with appropriate feature columns such as Crime rate (CRIM), proportion of residential land Zoned for large lots (ZN), average number of Rooms (RM), Nitrogen Oxide concentration (NOX), and others. To enhance predictive capabilities, a new feature representing the square of the average number of rooms (Rm_sq) was engineered and added to the feature set.

The dataset was split into training and testing subsets using a 70/30 ratio to evaluate model generalization. Three robust ensemble regression models were selected for this study: Random Forest, AdaBoost, and XGBoost. Each model was embedded within a pipeline that included data standardization (Using StandardScaler) to ensure proper scaling of features before model fitting. To optimize model performance, hyperparameter tuning was performed with GridSearchCV, employing 5-fold cross-validation. Hyperparameter grids included variations in the number of estimators, maximum tree depths, and learning rates depending on the model type. Additionally, training time for each model was measured to incorporate computational efficiency as a selection criterion.

Beyond predictive accuracy, the study incorporated two further criteria: training time and interpretability. Interpretability scores were assigned subjectively on a scale from 1 to 5 based on model transparency and ease of understanding, with AdaBoost considered more interpretable than Random Forest, and XGBoost the least.

To systematically combine these three evaluation criteria—accuracy (Measured inversely by cross-validated Mean Squared Error (MSE)), training time, and interpretability—the AHP was utilized to calculate relative weights. The pairwise comparison matrix reflected the relative importance of these criteria, resulting in weights approximately equal to 0.65 for accuracy, 0.23 for training time, and 0.12 for interpretability.

Normalization was applied differently according to whether a criterion was to be maximized or minimized. Since lower MSE and training time values indicate better performance, these metrics were inverted and normalized to be comparable with interpretability scores, which were normalized directly. A composite score for each model was then computed as a weighted sum of the normalized criteria, thereby reflecting a balanced evaluation that integrates performance, efficiency, and usability.

Finally, these composite scores were used as weights to construct a weighted Voting Regressor ensemble model, combining the strengths of the individual learners. The ensemble model, alongside individual optimized models, was evaluated on the holdout test dataset using MSE and Root Mean Squared Error (RMSE) metrics. This comprehensive methodology facilitates an informed and multi-dimensional selection of the best-performing model for housing price prediction, balancing accuracy with practical considerations such as speed and interpretability.

4 | Case Study: Housing Price Prediction Using Ensemble Learning and Analytic Hierarchy Process

4.1 | Dataset Description

This study employs the well-known Boston Housing dataset, containing 506 samples with 14 features. The target variable is the Median Value of owner-occupied homes (MEDV), expressed in thousands of dollars. Features include various economic and geographic indicators such as Crime rate (CRIM), proportion of residential land zoned for lots over 25,000 sq ft. (ZN), average number of Rooms (RM), Nitrogen Oxide concentration (NOX), among others.

Key data characteristics: Average house price (MEDV): 22.53 thousand dollars, Average number of Rooms (RM): 6.28. LSTAT, the percentage of lower-status population, shows a strong negative correlation (-0.74) with house prices. Data displays reasonable variance and distribution suitable for training ML models.

4.2 | Model Optimization and Training

Three popular and influential ensemble learning models—Random Forest, AdaBoost, and XGBoost—were used. Each model was tuned using GridSearchCV to optimize hyperparameters. Training time was also measured to account for the speed criterion.

Table 1. Optimized hyperparameters and training time for models.

Model	Best Parameters	Training Time (Seconds)
Random Forest	max_depth = 20, n_estimators = 100	16.29
AdaBoost	learning_rate = 0.1, n_estimators = 100	3.57
XGBoost	learning_rate = 0.1, max_depth = 3, n_estimators = 200	7.53

Table 1 presents the best-tuned hyperparameters for each model obtained via GridSearchCV, alongside the corresponding training times. AdaBoost exhibited the fastest training time, while Random Forest required the longest duration. XGBoost's training time lies between the two. These differences in training duration are essential considerations when selecting a model suitable for time-sensitive applications.

4.3 | Analytic Hierarchy Process for Criteria Weighting

Three key criteria were considered for model selection: Model Accuracy, Training Time, and Interpretability, using AHP, and the following weights were calculated:

Table 2. Criteria weights derived from the AHP.

Criterion	Weight (AHP)
Accuracy	0.648
Training time	0.230
Interpretability	0.122

Table 2 summarizes the relative importance of each evaluation criterion as determined by the AHP. Accuracy was identified as the most critical criterion, accounting for approximately 65% of the overall decision weight. Training time and interpretability also significantly contributed to the model selection process, with weights of about 23% and 12%, respectively. The use of AHP facilitates a structured, quantitative approach to balancing multiple evaluation factors, ensuring that model selection accounts for not only predictive performance but also computational efficiency and ease of understanding.

4.4 | Final Model Scores and Weighting for Ensemble Learning

Combining model results with criterion weights, the final scores for each model were:

Table 3. Final model scores based on AHP weighting.

Model	Final Score (AHP)
AdaBoost	0.387
XGBoost	0.338
Random Forest	0.275

Table 3 presents the overall scores of the evaluated ensemble learning models, calculated by integrating their performance metrics with the criterion weights obtained via the AHP. AdaBoost achieved the highest final score of 0.387, primarily due to its balance of training time efficiency and interpretability, despite having slightly lower predictive accuracy compared to XGBoost. XGBoost follows with a score of 0.338, benefiting from its high accuracy but offset by longer training times and lower interpretability. Random Forest scored 0.275, reflecting a trade-off between moderate accuracy and longer training duration. These results underscore the importance of multi-criteria evaluation in selecting ML models, beyond simply maximizing accuracy.

4.5 | Model Evaluation on Test Data

Models were evaluated using MSE and RMSE on the test dataset.

Table 4. Model evaluation metrics on the test dataset.

Model	MSE	RMSE
Random Forest	9.6395	3.1048
AdaBoost	16.8704	4.1074
XGBoost	8.1299	2.8513
Voting Ensemble	10.2869	3.2073

Table 4 summarizes the predictive performance of the evaluated models based on MSE and RMSE metrics on the held-out test data. Among the individual models, XGBoost achieved the lowest MSE and RMSE values, indicating superior predictive accuracy. However, when integrating multiple evaluation criteria, including training time and interpretability through the AHP, AdaBoost was ultimately selected as the preferred model due to its balanced trade-offs. The Voting Ensemble, which aggregates the predictions of all models weighted by their AHP scores, demonstrated acceptable overall performance but did not significantly outperform the best single model (XGBoost). This outcome underscores that ensemble methods, while powerful, may not always provide substantial gains across all evaluation dimensions in practical applications.

Although XGBoost provided the best accuracy, based on the multi-criteria AHP framework, AdaBoost was selected as the preferred model. The Voting Ensemble showed acceptable performance but no significant improvement over the best individual model.

5 | Conclusion

This study examined a combination of ensemble learning methods and the AHP for selecting the best model for housing price prediction. By considering accuracy, training speed, and interpretability criteria, and determining their weights using AHP, the final model selection reflects realistic preferences and the importance of each criterion. The results showed that although XGBoost provided the best prediction accuracy, AdaBoost was preferred due to its faster training time and higher interpretability within the MCDM framework of AHP. The Voting ensemble model with AHP-based weighting showed acceptable performance; however, careful tuning of weights is necessary to achieve an optimal combination of the advantages of base models. This approach illustrates that integrating ML techniques with MCDM methods can substantially assist in selecting practical and efficient models for real-world problems and opens avenues for future research in this area.

Author Contribution

The author contributed to the study design, theoretical formulation, computational coding, testing of the algorithm, performance evaluation, and preparation of the manuscript.

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Data Availability

The datasets used and analyzed in this study are fully presented within the article.

Conflicts of Interest

The author reports no potential conflict of interest.

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