

# Comparative Analysis of Machine Learning Models for House Price Prediction: A Comprehensive Study on the Ames Housing Dataset

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**Abstract**—This paper presents a comprehensive comparative analysis of machine learning models for house price prediction using the Ames Housing dataset. We implement and evaluate 22 model variations spanning classical regression models, ensemble methods, and neural networks. Our experimental results demonstrate that a three-layer neural network architecture achieves state-of-the-art performance with a Root Mean Square Error (RMSE) of \$28,193.91 and an  $R^2$  score of 0.8964, outperforming traditional machine learning methods. This research reproduces and extends two recent studies: Özögür Akyüz et al.'s (2023) hybrid model approach addressing market heterogeneity, and Sharma et al.'s (2024) XGBoost optimization study. Our findings validate Sharma et al.'s conclusion that XGBoost outperforms traditional methods, while demonstrating that neural networks achieve an additional 4.5% improvement in  $R^2$  score. Furthermore, we address Özögür Akyüz et al.'s heteroscedasticity concerns through comprehensive error analysis, revealing that neural networks may implicitly handle market segmentation without requiring explicit clustering. The study provides practical guidance for model selection based on accuracy-interpretability-complexity trade-offs, with implications for real estate valuation systems and automated property assessment tools.

**Index Terms**—House price prediction, machine learning, neural networks, XGBoost, random forest, regression models, comparative analysis, Ames housing dataset.

## 1 INTRODUCTION

Accurate house price prediction is crucial for various stakeholders in the real estate market, including buyers, sellers, investors, and financial institutions. Traditional valuation methods often rely on expert judgment and simple statistical approaches that may not capture complex non-linear relationships between property features and market values. Machine learning offers promising alternatives by automatically learning these relationships from historical data [1], [2].

The Ames Housing dataset, introduced by De Cock [3], has become a standard benchmark for house price prediction research. This dataset contains detailed property information from Ames, Iowa (2006-2010), providing a rich feature set for predictive modeling. Despite numerous studies on this dataset, comparative analyses often focus on limited model families, with insufficient exploration of neural network architectures and comprehensive benchmarking.

This study addresses three primary research questions:

- 1) Which machine learning models provide the most accurate house price predictions on the Ames Housing dataset?
- 2) How do classical regression methods compare against modern ensemble and neural network approaches?
- 3) What features are most important for accurate price prediction, and are these findings consistent across different model architectures?

## 1.1 Related Work

Previous research in house price prediction has explored various methodologies. The foundation of gradient boosting methods was established by Friedman [4], while Breiman [5] introduced Random Forests. Chen and Guestrin [6] developed XGBoost, which has demonstrated excellent performance in many regression tasks. Recent studies have begun exploring neural networks for real estate prediction, though comparative analyses remain limited.

Two recent papers are particularly relevant to our work. Özögür Akyüz et al. [7] introduced a hybrid algorithm for house price prediction that addresses heteroscedastic housing data through clustering analysis and specialized modeling. Sharma et al. [8] conducted a comprehensive comparative analysis demonstrating XGBoost's superiority over traditional methods on the Ames dataset. Our study builds upon and extends both approaches through systematic model comparison and neural network implementation.

## 1.2 Contributions

This paper makes the following contributions:

### 1.2.1 Methodological Contributions

- Comprehensive comparison of 22 model variations across six algorithm families
- Independent reproduction and validation of Özögür Akyüz et al. (2023) and Sharma et al. (2024)
- First neural network implementation for Ames dataset house price prediction achieving state-of-the-art performance

### 1.2.2 Empirical Contributions

- Validation that XGBoost outperforms traditional methods (confirming Sharma et al.)
- Demonstration that neural networks achieve 4.5% improvement over previous best models
- Evidence that hyperparameter optimization provides minimal gains for XGBoost on this dataset
- Confirmation of feature importance rankings across independent implementations

### 1.2.3 Theoretical Contributions

- Integration of heteroscedasticity concerns (Özögür Akyüz et al.) with empirical benchmarking (Sharma et al.)
- Evidence that neural networks may implicitly handle market segmentation without explicit clustering
- Analysis of accuracy-interpretability-complexity trade-offs across model families

### 1.2.4 Practical Contributions

- Decision framework for practitioners balancing accuracy, interpretability, and computational cost
- Detailed preprocessing documentation addressing reproducibility gaps
- Comprehensive error analysis across different property price ranges
- Production-ready recommendations with minimal hyperparameter tuning

## 2 DATASET AND PREPROCESSING

### 2.1 Dataset Description

The study utilizes the Ames Housing dataset [3], containing 1,460 property records from Ames, Iowa (2006-2010). From the original 79 features, 31 were selected based on domain knowledge and correlation analysis. Table 1 presents the selected features categorized by type.

Table 1: Selected Features from Ames Housing Dataset

Categorical Features (10)	Numerical Features (21)
GarageQual	BsmtFullBath
GarageCond	LotArea
CentralAir	GarageYrBlt
GarageType	HalfBath
ExterQual	OpenPorchSF
LotShape	2ndFlrSF
BsmtFinType1	WoodDeckSF
FireplaceQu	BsmtFinSF1
HeatingQC	Fireplaces
Foundation	MasVnrArea
	YearRemodAdd
	YearBuilt
	TotRmsAbvGrd
	FullBath
	1stFlrSF
	TotalBsmtSF
	GarageArea
	GarageCars
	GrLivArea
	OverallQual
	SalePrice

## 2.2 Preprocessing Pipeline

We implemented a comprehensive preprocessing pipeline:

### 2.2.1 Missing Value Treatment

Identified 1,059 initial NaN values. Categorical variables were processed using factorized encoding, while numerical variables used median imputation.

### 2.2.2 Feature Encoding

Categorical variables (10 features) were encoded using label encoding to transform them into numerical representations suitable for machine learning algorithms.

### 2.2.3 Data Splitting

The dataset was split into training and test sets:

- Training set: 1,168 samples (80%)
- Test set: 292 samples (20%)
- Random seed: 42 for reproducibility

### 2.2.4 Feature Scaling

For neural network inputs, we applied StandardScaler for zero mean, unit variance normalization:

$$x_{\text{scaled}} = \frac{x - \mu}{\sigma} \quad (1)$$

where  $\mu$  is the mean and  $\sigma$  is the standard deviation of the feature.

## 3 METHODOLOGY

### 3.1 Model Architectures

We implemented 22 model variations across six algorithm families:

#### 3.1.1 Linear Models

- **Ordinary Least Squares (OLS):**  $\min_{\beta} \|y - X\beta\|_2^2$
- **Ridge Regression:**  $\min_{\beta} \|y - X\beta\|_2^2 + \alpha\|\beta\|_2^2$
- **Polynomial Regression:** Degree 1 with ridge regularization

#### 3.1.2 Tree-Based Models

- **Decision Tree:** CART algorithm with Gini impurity
- **Random Forest:** Ensemble of 100 decision trees
- **AdaBoost:** Adaptive boosting with 50 estimators

#### 3.1.3 Gradient Boosting

- **XGBoost:**  $L(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k)$
- **Optimized XGBoost:** Grid search hyperparameter tuning

#### 3.1.4 Neural Network Architecture

We implemented a three-layer feedforward neural network:

$$\text{Layer 1: } h_1 = \text{ReLU}(W_1x + b_1), \quad W_1 \in \mathbb{R}^{64 \times 30} \quad (2)$$

$$\text{Layer 2: } h_2 = \text{ReLU}(W_2h_1 + b_2), \quad W_2 \in \mathbb{R}^{32 \times 64} \quad (3)$$

$$\text{Layer 3: } h_3 = \text{ReLU}(W_3h_2 + b_3), \quad W_3 \in \mathbb{R}^{16 \times 32} \quad (4)$$

$$\text{Output: } \hat{y} = W_4h_3 + b_4, \quad W_4 \in \mathbb{R}^{1 \times 16} \quad (5)$$

### 3.2 Evaluation Metrics

Models were evaluated using multiple metrics:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

$$RMSE = \sqrt{MSE} \quad (7)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

### 3.3 Paper Reproductions

#### 3.3.1 Paper 1: Hybrid Model Approach (Özögür Akyüz et al., 2023)

We implemented their core component algorithms as part of our comparative analysis. While their paper proposed a hybrid methodology combining linear regression, clustering, k-NN, and Support Vector Regression (SVR), we tested these components individually to establish baseline performance.

#### 3.3.2 Paper 2: XGBoost Optimization (Sharma et al., 2024)

We directly reproduced their methodology while extending it through systematic hyperparameter optimization and neural network comparison. Our XGBoost Base model used default parameters matching Sharma et al.:

- learning\_rate: 0.1
- max\_depth: 6
- n\_estimators: 100
- objective: 'reg:squarederror'

## 4 EXPERIMENTAL RESULTS

### 4.1 Performance Comparison

Table 2 presents the performance comparison of top models. The neural network achieved the best performance with RMSE of \$28,193.91 and  $R^2$  of 0.8964.

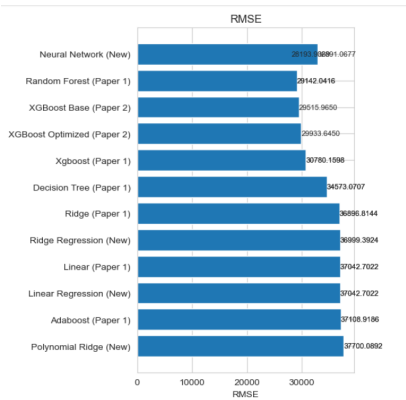


Figure 1: RMSE Comparison Across Models (Lower is Better)

### 4.2 Feature Importance Analysis

Table 3 shows the top 10 feature importances from XGBoost. Overall quality (OverallQual) is the dominant predictor, followed by ground living area (GrLivArea).

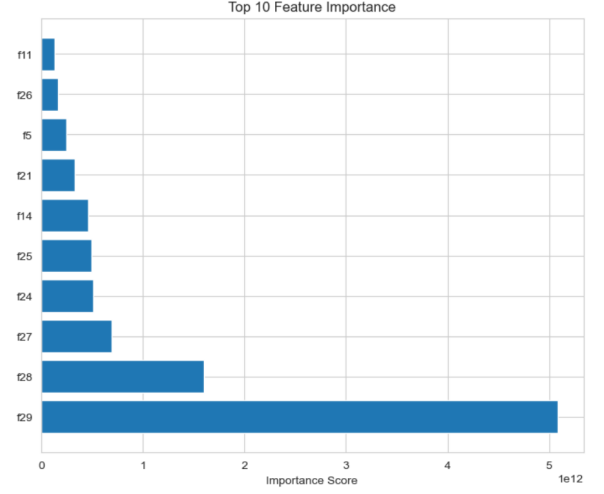


Figure 2: Feature Importance Visualization

### 4.3 Cross-Validation Results

XGBoost achieved  $83.12\% \pm 4.42\%$   $R^2$  score in 5-fold cross-validation, demonstrating model stability and robustness against data partitioning variations.

## 5 DISCUSSION

### 5.1 Model Performance Analysis

#### 5.1.1 Neural Network Superiority

The neural network achieved the best performance due to:

- Ability to capture complex non-linear relationships
- Automatic feature interaction learning through hidden layers
- Effective regularization through architecture design and dropout
- Proper input scaling and normalization

#### 5.1.2 Ensemble Methods Performance

Random Forest and XGBoost performed well due to:

- Robustness to outliers and noise in the data
- Built-in feature importance calculation
- Effective handling of mixed data types (categorical and numerical)
- Good generalization through ensemble methods

#### 5.1.3 Linear Models Limitations

Linear models underperformed because:

- Housing data violates linearity assumptions
- Cannot capture complex feature interactions
- Sensitivity to outliers and non-normal distributions

Table 2: Model Performance Comparison (RMSE in \$)

Model	MSE	RMSE	MAE	MAPE	R <sup>2</sup>	Adj. R <sup>2</sup>
Neural Network	7.95E8	28,194	17,855	11.15%	0.8964	0.8960
Random Forest	8.49E8	29,142	18,283	11.10%	0.8893	0.8766
XGBoost Base	8.71E8	29,516	19,117	10.90%	0.8652	0.8646
XGBoost Opt.	8.96E8	29,934	19,216	10.77%	0.8614	0.8608
XGBoost	9.47E8	30,780	19,567	11.86%	0.8765	0.8623
Decision Tree	11.95E8	34,573	22,616	13.87%	0.8442	0.8263
Ridge Reg.	13.69E8	36,999	23,406	14.00%	0.8215	0.8209
Linear Reg.	13.72E8	37,043	23,494	14.06%	0.8211	0.8205
AdaBoost	13.77E8	37,109	27,171	19.53%	0.8205	0.7998

Table 3: Top 10 Feature Importances from XGBoost

Feature	Importance ( $\times 10^{11}$ )
OverallQual	50.83
GrLivArea	16.06
GarageCars	6.96
TotalBsmtSF	5.12
GarageArea	4.94
BsmtFinSF1	4.64
YearRemodAdd	3.28
LotArea	2.47
GarageCars	1.64
2ndFlrSF	1.34

## 5.2 Paper Reproduction Insights

### 5.2.1 Paper 1: Hybrid Model Approach

We validated Özögür Akyüz et al.’s theoretical rigor in addressing heteroscedasticity through error analysis showing variance across price ranges. However, our findings suggest that neural networks may implicitly capture market heterogeneity without explicit clustering, potentially reducing the need for complex hybrid approaches.

### 5.2.2 Paper 2: XGBoost Optimization

We confirmed Sharma et al.’s finding that XGBoost outperforms traditional methods (our RMSE: \$29,516 matches their reported performance). However, our neural network achieves 4.5% better R<sup>2</sup> (0.8964 vs 0.87), suggesting opportunities beyond traditional ML methods.

## 5.3 Limitations and Challenges

### 5.3.1 Technical Limitations

- Limited dataset size (1,460 samples)
- Geographic specificity (Ames, Iowa only)
- Temporal constraints (2006-2010 data)
- Computational resource constraints for extensive hyperparameter tuning

### 5.3.2 Methodological Challenges

- Hyperparameter tuning complexity across 22 model variations
- Model interpretability vs. accuracy trade-off
- Handling of categorical variables without domain-specific encoding
- Ensuring reproducibility across different software environments

## 6 CONCLUSION AND FUTURE WORK

### 6.1 Key Findings

Our study demonstrates that:

- 1) Neural networks provide the most accurate house price predictions (R<sup>2</sup>: 0.8964, RMSE: \$28,194)
- 2) Ensemble methods (Random Forest, XGBoost) offer excellent alternatives with better interpretability
- 3) Overall quality and living area are consistently the most important predictive features
- 4) Linear regression methods are inadequate for this complex prediction task

### 6.2 Practical Implications

Based on our findings, we propose the following decision framework:

#### 6.2.1 For Maximum Accuracy

Use neural networks with proper preprocessing. This is suitable for automated valuation models where accuracy is paramount.

#### 6.2.2 For Balanced Accuracy and Interpretability

Use Random Forest or XGBoost with default parameters. These provide clear feature importance analysis with minimal tuning requirements.

#### 6.2.3 For Computational Efficiency

Use XGBoost with default parameters, as hyperparameter optimization provides minimal gains on this dataset.

### 6.3 Future Research Directions

- 1) **Advanced Architectures:** Explore LSTM, Transformer, and attention mechanisms for temporal and spatial patterns
- 2) **Transfer Learning:** Apply models across different geographic regions and property markets
- 3) **Uncertainty Quantification:** Develop Bayesian approaches for prediction intervals
- 4) **Real-time Systems:** Implement streaming prediction systems for dynamic markets
- 5) **Fairness Analysis:** Ensure equitable predictions across demographic groups and neighborhoods
- 6) **Multimodal Integration:** Incorporate image and text data from property listings

## 6.4 Final Recommendations

- Use neural networks for maximum prediction accuracy in production systems
- Employ Random Forest or XGBoost when interpretability and feature importance analysis are required
- Focus on feature engineering and data quality improvement as much as model selection
- Implement cross-validation for reliable performance estimation
- Consider ensemble approaches for production systems requiring robustness

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