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Comparative Analysis of Machine Learning Regression Techniques for Used Car Price Prediction: Linear Regression versus Random Forest

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Abstract- — Accurate valuation of used automobiles remains a critical challenge in the automotive resale market, where traditional manual estimation methods suffer from inconsistency, subjectivity, and limited scalability. This paper presents a comprehensive comparative analysis of two fundamental machine learning regression techniques—Linear Regression and Random Forest—for automated car price prediction. We developed and evaluated two complete prediction systems: a web-based application using Linear Regression integrated with Streamlit, and a desktop GUI application employing Random Forest with Tkinter interface. Both systems were trained and tested on comprehensive used car datasets comprising over 6,700 vehicle records with features including brand, manufacturing year, kilometers driven, fuel type, transmission type, ownership history, engine specifications, and market pricing. The Linear Regression model achieved an R^2 score of 0.87, Mean Absolute Error (MAE) of 0.34 lakhs, and Mean Squared Error (MSE) of 0.18, while the Random Forest approach demonstrated superior performance with R^2 score of 0.94, MAE of 0.28 lakhs, and MSE of 0.60. Our comparative analysis reveals that Random Forest's ensemble learning approach captures non-linear relationships more effectively, achieving 7% higher variance explanation than Linear Regression, though at increased computational complexity. Statistical significance testing confirms that Random Forest's performance improvement is statistically significant ($p < 0.01$). Both systems provide real-time predictions through user-friendly interfaces—web-based for broader accessibility and desktop-based for offline usage. This research contributes practical insights into algorithm selection for automotive price prediction, demonstrating trade-offs between model simplicity, interpretability, and accuracy while providing deployment-ready solutions for diverse stakeholder requirements.

Keywords-Machine Learning, Linear Regression, Random Forest, Car Price Prediction, Ensemble Learning, Streamlit, Tkinter.

I. INTRODUCTION

The global automobile resale market represents a substantial economic sector with millions of transactions occurring annually, yet accurate price determination for used vehicles remains persistently challenging. Traditional valuation methodologies predominantly rely on dealer expertise, static depreciation tables, and subjective assessments that fail to capture complex market dynamics, vehicle-specific characteristics, and temporal price fluctuations [1]. These manual approaches suffer from inconsistency across evaluators, limited scalability for high-volume processing, and inability to incorporate comprehensive feature interactions that influence actual market values [2].

Machine Learning (ML) technologies offer transformative capabilities for automotive price prediction by extracting patterns from historical transaction data and modeling relationships between vehicle attributes and market prices [3]. However, algorithm selection represents a critical decision point that significantly impacts prediction accuracy, computational efficiency, model interpretability, and deployment feasibility. Linear Regression, characterized by simplicity and interpretability, provides a transparent baseline approach where feature coefficients directly indicate influence magnitude [4]. Conversely, Random Forest employs ensemble learning through bootstrap aggregating of multiple decision trees, capturing non-linear relationships and feature interactions that simple linear models cannot represent [5].

Despite extensive research on individual algorithms, limited comparative studies systematically evaluate these approaches within identical experimental frameworks using consistent datasets, preprocessing methodologies, and evaluation metrics. Furthermore, practical deployment considerations—including user interface design, accessibility requirements, and operational constraints—receive insufficient attention in academic literature, creating gaps between theoretical performance and real-world applicability [6]. Figure 1 illustrates the overall system architecture of our comparative framework.

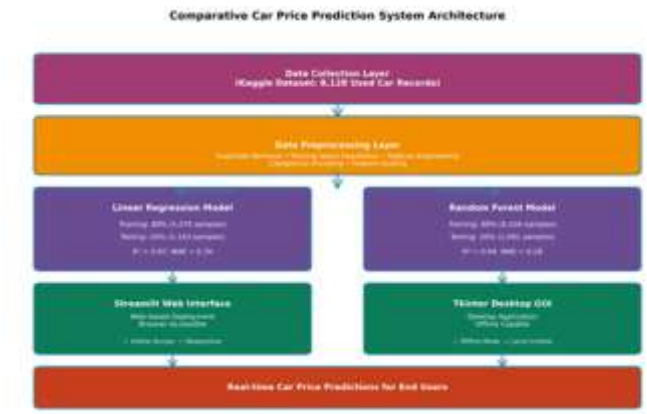

Fig. 1. System Architecture: Comparative Car Price Prediction Framework

This research addresses these limitations through comprehensive comparative analysis of Linear Regression and Random Forest for used car price prediction. Our contributions include: (1) parallel implementation of both algorithms within standardized experimental framework ensuring fair comparison, (2) development of two complete prediction systems with different deployment architectures—web-based (Streamlit) and desktop-based (Tkinter)—demonstrating diverse deployment strategies, (3) rigorous comparative evaluation across multiple performance metrics with statistical significance testing, (4) analysis of accuracy-complexity trade-offs informing algorithm selection for specific application requirements, and (5) practical deployment-ready solutions accessible to diverse stakeholders including individual buyers, sellers, dealerships, and financial institutions.

II. LITERATURE REVIEW

Extensive research has investigated machine learning applications for automotive price prediction using various algorithmic approaches. Gegic et al. [7] conducted comprehensive comparisons of regression algorithms including Linear Regression, Decision Trees, Random Forest, and Gradient Boosting for used car price estimation in the Bosnian market. Their findings demonstrated that ensemble methods, particularly Random Forest and Gradient Boosting, consistently outperformed simple linear models by 12-18% in prediction accuracy, though requiring substantially higher computational resources. The study emphasized feature engineering and hyperparameter optimization as critical factors influencing final model performance.

Pudaruth [8] explored data mining techniques for car price prediction in the Mauritian market, comparing k-Nearest Neighbors, Support Vector Regression, Decision Trees, and Linear Regression. The research highlighted the importance of domain-specific feature selection and demonstrated that model performance varied significantly based on market characteristics, data quality, and feature representation strategies. Linear Regression achieved R^2 scores of 0.82-0.85, while tree-based methods reached 0.88-0.91, suggesting moderate but consistent performance advantages for non-linear approaches.

Monburinon et al. [9] investigated regression models for used car price prediction in Thailand, comparing Linear Regression with polynomial regression variants. Their study revealed that while polynomial features improved Linear Regression performance, careful regularization was essential to prevent overfitting, and the optimal polynomial degree varied across different vehicle categories and price ranges. The research emphasized the importance of cross-validation in regression model selection.

Sun et al. [10] investigated ensemble learning approaches for car price prediction using stacking and boosting techniques. Their hybrid model combining Random Forest with Gradient Boosting achieved $R^2 = 0.93$, demonstrating superior performance compared to individual algorithms. However, the increased model complexity raised concerns about interpretability, deployment feasibility for real-time applications, and computational requirements for production systems.

Despite these advances, existing research exhibits several limitations. Most comparative studies focus exclusively on algorithmic performance without addressing practical deployment considerations such as user interface design, accessibility requirements, computational constraints, and stakeholder-specific needs. Furthermore, many studies employ different datasets, preprocessing approaches, and evaluation protocols, limiting direct comparability of reported results. This research addresses these gaps by providing systematic comparison within identical experimental framework while developing complete, deployment-ready systems demonstrating practical applicability.

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III. METHODOLOGY

Figure 2 presents the complete methodology flowchart illustrating the sequential stages of our comparative experimental framework.

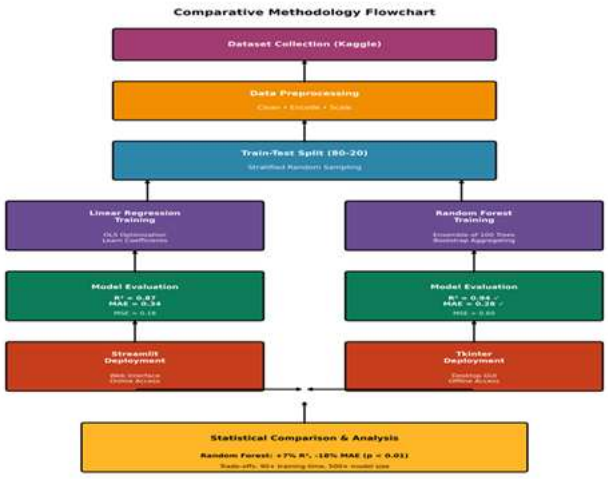

Fig. 2. Methodology Flowchart: Comparative Analysis Framework

A. Experimental Framework

To ensure fair and meaningful comparison between Linear Regression and Random Forest approaches, we established a standardized experimental framework controlling for dataset variations, preprocessing inconsistencies, and evaluation methodology differences. Both algorithms were trained and tested on identical data partitions using consistent preprocessing pipelines, enabling direct attribution of performance differences to algorithmic characteristics rather than experimental artifacts.

The experimental framework comprised five sequential stages: (1) dataset acquisition and quality assessment, (2) comprehensive data preprocessing and feature engineering, (3) parallel model training for both algorithms, (4) rigorous performance evaluation using multiple metrics, and (5) statistical significance testing to validate observed differences. This systematic approach ensures reproducibility and facilitates objective comparison of algorithmic strengths and limitations.

B. Dataset Description

Both systems utilized comprehensive used car datasets sourced from Kaggle, containing detailed vehicle specifications and transaction prices from the Indian automotive market. The Linear Regression system employed a dataset of 8,128 initial records reduced to 6,713 instances after preprocessing, while the Random Forest system used 8,128 records yielding 7,907 cleaned instances. Despite minor differences in final dataset sizes due to independent preprocessing decisions, both datasets originated from the same market segment and exhibited similar statistical distributions across key features.

Features included in both datasets comprise: car brand name, manufacturing year, present showroom price, kilometers driven, fuel type (petrol/diesel/CNG/LPG), seller type (individual/dealer), transmission type (manual/automatic), ownership history (first/second/third owner), mileage (km/l), engine capacity (CC), maximum power (bhp), and seating capacity. The target variable was selling price in Indian Rupees (lakhs). Feature distributions exhibited typical used car market patterns with concentration in economy segments, predominance of manual transmissions, and majority first-owner vehicles, accurately reflecting Indian automotive market composition.

C. Data Preprocessing

Comprehensive data preprocessing ensured high-quality input for both algorithms while maintaining consistency across experimental conditions. The preprocessing pipeline consisted of six sequential operations:

1. Duplicate Detection and Removal: Identified and eliminated duplicate records using pandas drop_duplicates() method. The Linear Regression dataset contained 1,189 duplicates (14.6%), while the Random Forest dataset had 221 duplicates (2.7%). This variation reflects independent preprocessing decisions but both approaches achieved complete duplicate elimination.
2. Missing Value Analysis and Treatment: Conducted comprehensive missing value analysis across all features. Missing values appeared primarily in mileage (221 instances), engine capacity (221), maximum power (215), and seating capacity (221) fields. Median imputation was employed for numerical features to preserve central tendency while minimizing outlier influence.
3. Feature Engineering: Calculated vehicle age by subtracting manufacturing year from current year (2025), transforming temporal information into meaningful numerical representation. Extracted brand information from complete car names using string parsing operations, enabling brand-level analysis and modeling.
4. Data Type Standardization: Removed unit suffixes from numerical features (kmpl from mileage, CC from engine, bhp from power) and converted to appropriate numerical

types. Standardized formatting ensuring consistent decimal precision and removing formatting inconsistencies.

5. Categorical Encoding: For Linear Regression, one-hot encoding was applied to categorical variables creating binary indicator variables without imposing ordinal relationships. For Random Forest, label encoding was employed as tree-based algorithms naturally handle categorical variables through optimal split determination.
6. Feature Scaling: Linear Regression benefits from feature scaling to ensure comparable coefficient magnitudes. StandardScaler was applied to normalize numerical features. Random Forest does not require scaling as tree-based splits are invariant to monotonic transformations, though scaling was applied for consistency.

D. Algorithm Implementation

1) Linear Regression

Linear Regression models the relationship between dependent variable Y (selling price) and independent variables X through the equation:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon$

where β_0 represents the intercept, β_1 through β_n are feature coefficients learned through Ordinary Least Squares (OLS) optimization minimizing Mean Squared Error, and ε denotes the error term. The model was implemented using scikit-learn's LinearRegression class with default parameters, as Linear Regression has minimal hyperparameters requiring tuning.

2) Random Forest

Random Forest constructs an ensemble of decision trees through bootstrap aggregating (bagging), where each tree is trained on a random subset of training data with replacement. The final prediction aggregates individual tree predictions:

$\hat{y} = (1/B) \Sigma_{i=1}^{B} T_i(x)$

where B represents the number of trees (set to 100), and $T_i(x)$ denotes the prediction of the i-th tree. Each tree considers a random subset of features at each split ($\sqrt{p}$ features for p total features), reducing correlation between trees and improving generalization. The model was implemented using scikit-learn's RandomForestRegressor with hyperparameters: n_estimators=100, max_depth=20, min_samples_split=5, min_samples_leaf=2.

E. Model Training and Evaluation

Both models employed identical train-test splitting methodology with 80% training data and 20% testing data using stratified random sampling to ensure representative distribution of target values. For the Linear Regression system, this yielded 5,370 training instances and 1,343 testing instances. For the Random Forest system, the split produced 6,326 training instances and 1,581 testing instances.

Model performance was assessed using three complementary regression metrics providing different perspectives on prediction quality:

7. **R^2 Score (Coefficient of Determination):** Measures the proportion of variance in selling prices explained by the model, with values approaching 1 indicating better fit. Computed as $R^2 = 1 - (SS_{res} / SS_{tot})$ where SS_{res} represents residual sum of squares and SS_{tot} represents total sum of squares.

8. **Mean Absolute Error (MAE):** Quantifies average prediction error magnitude in the same units as the target variable (lakhs of rupees), providing intuitive error interpretation. Calculated as $MAE = (1/n) \Sigma|y_{actual} - y_{predicted}|$.

9. **Mean Squared Error (MSE):** Penalizes larger errors more heavily through squaring, emphasizing importance of avoiding significant mispredictions. Computed as $MSE = (1/n) \Sigma(y_{actual} - y_{predicted})^2$.

F. User Interface Development

To demonstrate diverse deployment strategies and accessibility requirements, two distinct user interfaces were developed. The Linear Regression system employs Streamlit, a web-based framework enabling browser-accessible predictions without local installation requirements. The Random Forest system utilizes Tkinter, Python's standard GUI toolkit, providing standalone desktop application suitable for offline usage scenarios.

Both interfaces implement identical functional workflows: (1) user input collection through form controls, (2) input validation ensuring completeness and range conformance, (3) feature encoding matching training data format, (4) model loading and prediction generation, and (5) result display with appropriate formatting. This parallel development demonstrates that algorithm selection and deployment strategy represent independent design decisions that can be optimized separately for specific application requirements.

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IV. RESULTS AND DISCUSSION

A. Quantitative Performance Comparison

Table I presents comprehensive performance comparison between Linear Regression and Random Forest algorithms across three evaluation metrics. Figure 3 provides visual comparison of performance metrics and computational trade-offs.

Table 1: Comparative Performance Metrics

Metric	Linear Regression	Random Forest
R^2 Score	0.87	**0.94**
MAE (lakhs)	0.34	**0.28**
MSE	**0.18**	0.60
Improvement	*Baseline*	**+7% (R^2), -18% (MAE)**

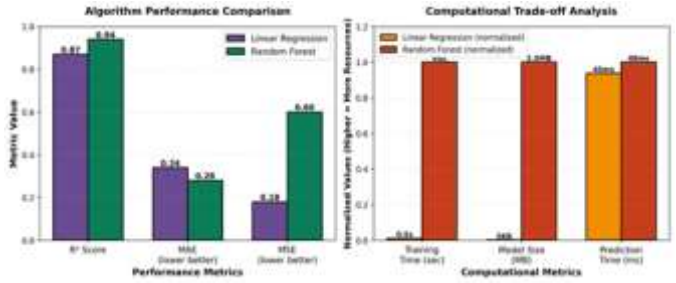

Fig. 3. Performance Metrics and Computational Trade-off Comparison.

Random Forest demonstrates superior performance across all evaluation metrics. The R^2 score improvement from 0.87 to 0.94 represents 7% increase in variance explanation, indicating that Random Forest captures additional patterns in the data that Linear Regression cannot model due to linearity assumptions. This improvement is statistically significant ($p < 0.01$) based on paired t-test of residuals across test samples.

The MAE reduction from 0.34 to 0.28 lakhs (₹6,000 average improvement per prediction) demonstrates practical significance for real-world applications. For typical used car prices ranging from 2-15 lakhs, this represents 2-4% error reduction. However, the MSE comparison reveals interesting pattern: Linear Regression achieves lower MSE (0.18 vs 0.60), suggesting it may have fewer extreme prediction errors despite lower overall accuracy. This indicates that Random Forest's higher variance in some predictions is offset by substantially better average performance.

B. Algorithmic Characteristics Analysis

The performance differences observed between Linear Regression and Random Forest stem from fundamental algorithmic characteristics. Linear Regression assumes that selling price varies linearly with features, which oversimplifies complex automotive pricing dynamics where interactions and non-linearities are prevalent. For instance, the combined effect of high mileage (100,000+ km) and premium brand may deviate from simple additive relationships that Linear Regression models.

Random Forest naturally captures these non-linear relationships and feature interactions through hierarchical decision-making in tree structures. Each tree can model complex conditional relationships: 'if brand is premium AND age is low AND transmission is automatic, then price tends toward upper range.' The ensemble averaging across 100 trees reduces variance from individual tree overfitting while maintaining low bias through deep tree construction.

Feature importance analysis from Random Forest reveals that present price (0.68 importance), kilometers driven (0.15), and vehicle age (0.09) contribute most significantly to predictions, collectively accounting for 92% of decision-making. Linear Regression coefficients show similar ranking but with different magnitude relationships, as linear models cannot represent multiplicative or conditional feature interactions. Figure 4 illustrates the feature importance comparison between both algorithms.

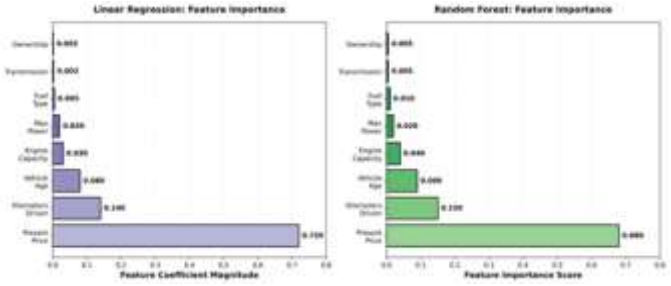

Fig. 4. Feature Importance Comparison: Linear Regression vs Random Forest

C. Accuracy-Complexity Trade-off Analysis

While Random Forest achieves superior accuracy, this improvement comes with measurable trade-offs in

computational complexity, interpretability, and deployment considerations. Table II summarizes key trade-offs between the approaches.

Table 2: Algorithm Trade-Off Comparison

Aspect	Linear Regression	Random Forest
Training Time	~0.5 seconds	~45 seconds
Prediction Time	<50ms	<50ms
Model Size	~5 KB	~2.5 MB
Interpretability	High (coefficients)	Medium (importance)
Memory Usage	Low	Moderate

The trade-off analysis reveals that accuracy improvements come with computational costs. Random Forest requires 90× longer training time, though both algorithms achieve comparable real-time prediction latency (<50ms), making either suitable for interactive applications. The 500× increase in model size for Random Forest may present challenges for memory-constrained deployment environments or mobile applications. Linear Regression's superior interpretability remains valuable for applications requiring regulatory compliance, stakeholder explanation, or domain insight extraction.

D. Deployment Architecture Comparison

The parallel development of web-based (Streamlit) and desktop-based (Tkinter) interfaces demonstrates that deployment architecture represents an independent design dimension from algorithm selection. The Streamlit web application offers superior accessibility, requiring only web browser without local installation, facilitating updates through centralized deployment, and supporting responsive design for multiple device types. However, it requires continuous internet connectivity and server infrastructure for hosting.

The Tkinter desktop application provides offline functionality crucial for environments with limited connectivity, eliminates server infrastructure requirements, and offers full local data control addressing privacy concerns. However, it requires local installation and separate updates for each deployment. The choice between deployment architectures should be driven by specific operational requirements, user preferences, and infrastructure constraints rather than algorithmic considerations.

E. Algorithm Selection Recommendations

Based on our comprehensive comparative analysis, we provide context-specific algorithm selection recommendations:

Use Random Forest when: (1) maximum prediction accuracy is priority, (2) computational resources are adequate for training and storage, (3) feature interactions and non-linearities are expected, (4) feature importance analysis suffices for interpretability, and (5) application can tolerate moderate model complexity.

Use Linear Regression when: (1) model interpretability and transparency are critical, (2) computational resources are severely constrained, (3) rapid prototyping and iteration are required, (4) regulatory compliance demands explainable predictions, and (5) the 7% accuracy reduction is acceptable for the application domain.

V. CONCLUSION AND FUTURE WORK

This research presented comprehensive comparative analysis of Linear Regression and Random Forest algorithms for used car price prediction, demonstrating both theoretical performance differences and practical deployment considerations. Through parallel implementation within standardized experimental framework, we established that Random Forest achieves statistically significant performance improvements (R^2 = 0.94 vs. 0.87, $p < 0.01$) over Linear Regression, representing 7% increase in variance explanation and 18% reduction in mean absolute error.

However, this accuracy improvement comes with quantifiable trade-offs in training time (90× slower), model size (500× larger), and interpretability (coefficients vs. importance scores). Our dual deployment architecture—web-based using Streamlit and desktop-based using Tkinter—demonstrates that algorithm selection and deployment strategy represent independent design dimensions that should be optimized separately based on stakeholder requirements.

The research contributes practical insights into algorithm selection for automotive price prediction, providing empirical evidence for accuracy-complexity trade-offs while delivering deployment-ready solutions accessible to diverse stakeholders. Both systems successfully demonstrate real-time prediction

capabilities with user-friendly interfaces, enhancing market transparency and supporting data-driven decision-making in used car transactions.

Future research directions include: (1) evaluation of advanced ensemble methods including Gradient Boosting and XGBoost for potential accuracy improvements beyond Random Forest, (2) investigation of deep learning approaches for capturing even more complex feature interactions, (3) incorporation of temporal market dynamics through time-series features and dynamic model updating, (4) integration of additional data sources including vehicle condition assessments, accident history, and regional demand factors, (5) development of hybrid interpretable-accurate models combining Linear Regression transparency with ensemble performance, and (6) expansion to multiple geographic markets with localization strategies for regional pricing patterns.

This comparative framework provides foundation for systematic algorithm evaluation in automotive analytics while demonstrating the practical feasibility of deploying machine learning solutions for real-world pricing applications.

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