e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:02/February-2025 Impact Factor- 8.187 www.irjmets.com

IMPROVED PROFITABILITY THROUGH RESIDUAL VALUE ANALYSIS: PREDICTIVE MODELING FOR VEHICLE PRICING AND MARKET STRATEGIES

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DOI : https://www.doi.org/10.56726/IRJMETS67571

ABSTRACT

An innovative approach to residual value prediction in the automotive industry demonstrates how advanced machine learning techniques can improve valuation accuracy. Moving beyond traditional forecasting methods, sophisticated AI-driven models have transformed leasing operations, pricing strategies, and market performance. Through deep learning architectures and ensemble methods, significant improvements in prediction accuracy emerge across various vehicle segments, particularly in handling complex market dynamics and emerging technologies like electric vehicles. The integration of multiple data sources, real-time analysis, and specialized modeling techniques enhances residual value forecasting, offering practical solutions for automotive sector challenges.

Keywords: Machine Learning Applications, Automotive Valuation, Electric Vehicle Analytics, Predictive Algorithms, Market Performance Optimization.

I. INTRODUCTION

The automotive industry's financial landscape has been fundamentally transformed by the critical role of residual value forecasting. According to recent market analysis, the global vehicle leasing market was valued at USD 92.1 billion in 2021 and is projected to reach USD 123.87 billion by 2027, exhibiting a compound annual growth rate (CAGR) of 7.2% during this period [1]. This remarkable growth trajectory has been driven by increasing consumer preference for operational leasing and a surge in demand for commercial vehicle leasing across emerging economies. The market dynamics have been particularly influenced by the rise of electric vehicles, with major automotive manufacturers investing heavily in EV fleets for leasing operations.

Accurate residual value forecasting stands as a cornerstone of effective automotive industry management, particularly in leasing portfolio administration and used vehicle market operations. Traditional forecasting methods have shown significant limitations, as evidenced by the U.S. Department of Energy's comprehensive analysis of vehicle depreciation patterns. Their research indicates that conventional prediction models have failed to accurately account for the rapid technological advancement in the automotive sector, leading to systematic undervaluation of electric vehicles by 10-15% and overvaluation of certain internal combustion engine vehicles by 8-12% [2]. These discrepancies have resulted in substantial financial implications, with the industry facing an estimated $2.8 billion in valuation adjustments during 2021 alone.

The market landscape has become increasingly complex with the introduction of new powertrain technologies and changing consumer preferences. Recent data from vehicle remarketing channels shows that electric vehicles retain approximately 48-55% of their original value after three years, compared to 45-50% for conventional vehicles, varying significantly by region and model [1]. This variation has created new challenges for traditional forecasting methods, which typically rely on historical depreciation curves that may no longer accurately reflect current market conditions.

Our research introduces cutting-edge predictive modeling approaches designed to enhance residual value estimation accuracy. The methodology incorporates real-time market data analysis and advanced machine learning algorithms, achieving prediction accuracy improvements of up to 13.5% compared to conventional methods. This enhanced accuracy is particularly crucial given the Department of Energy's findings that residual value miscalculations can impact fleet operators' total cost of ownership by up to 24% over a vehicle's lifecycle [2].

The significance of accurate residual value prediction is further underscored by the shifting dynamics in vehicle financing. The leasing market has witnessed a substantial transformation, with corporate leasing accounting for approximately 42% of the total market share in 2021, and this segment is expected to grow at a CAGR of 8.1%

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through 2027 [1]. These market conditions have created an unprecedented need for more sophisticated forecasting tools that can adapt to rapidly evolving market conditions and technological advancements.

II. LITERATURE REVIEW

2.1 Residual Value and Its Importance

Residual value forecasting has become increasingly crucial in automotive financial planning, with studies showing that lease penetration rates in mature markets have reached up to 30% of new vehicle sales. According to comprehensive research utilizing artificial neural networks for residual value prediction, the accuracy of these forecasts directly impacts both manufacturers and lessors, with prediction errors potentially affecting portfolio values by €500-€2,500 per vehicle in the European market [3]. The significance of precise residual value estimation is particularly evident in premium vehicle segments, where the absolute monetary impact of prediction errors is substantially higher due to greater initial vehicle values.

Recent analyses demonstrate that residual values exhibit complex patterns of depreciation, with the most significant value loss occurring in the first three years of vehicle life, showing an average depreciation of 30-40% depending on the vehicle segment and market conditions. The research indicates that luxury vehicles typically maintain higher residual values, with premium German manufacturers showing 5-8% better value retention compared to volume brands [3]. These variations in depreciation patterns have substantial implications for lease pricing and risk management strategies across different market segments.

2.2 Traditional Approaches to Residual Value Estimation

Conventional residual value estimation methodologies have predominantly relied on linear regression models and expert-based systems. Recent research in machine learning applications for automotive pricing has revealed that these traditional approaches achieve mean accuracy rates of approximately 76% when predicting three-year residual values [4]. The limitations of these conventional methods become particularly apparent when dealing with market disruptions and rapid technological changes in the automotive sector.

Market analysis from extensive vehicle pricing datasets shows that traditional forecasting methods struggle to account for the increasing complexity of modern automotive markets. The research reveals that conventional approaches demonstrate mean absolute percentage errors (MAPE) ranging from 8% to 15% when predicting residual values for electric vehicles, compared to 6-9% for internal combustion engine vehicles [4]. This discrepancy is particularly significant given the accelerating adoption of electric vehicles and the unique depreciation patterns they exhibit.

2.3 Predictive Modeling in the Automotive Industry

The integration of advanced machine learning techniques has revolutionized residual value forecasting capabilities. Neural network models, particularly Multi-Layer Perceptrons (MLPs) with optimized architectures, have demonstrated remarkable improvements in prediction accuracy. Research shows that artificial neural networks can achieve mean absolute percentage errors as low as 3.5% for standard vehicle configurations, representing a significant improvement over traditional methods [3]. These advanced models have proven particularly effective in capturing non-linear relationships between various market factors and residual values.

Contemporary predictive modeling approaches have evolved to incorporate sophisticated analytical frameworks. Deep learning models utilizing temporal convolutional networks have shown exceptional promise in capturing both short-term market fluctuations and long-term depreciation trends. Recent studies implementing advanced machine learning algorithms have achieved R-squared values of up to 0.91 for residual value predictions, with particularly strong performance in markets with high data availability [4]. The research indicates that ensemble methods combining multiple algorithmic approaches can further reduce prediction errors by up to 23% compared to single-model implementations.

The advancement in predictive modeling capabilities has been particularly significant in handling complex market dynamics. Studies show that modern machine learning models can effectively process over 50 distinct variables influencing residual values, including macroeconomic indicators, regional market conditions, and vehicle-specific attributes. The integration of these comprehensive data sets has enabled prediction accuracies exceeding 85% for three-year residual value forecasts across diverse vehicle segments [4].

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Table 1: Performance Metrics of Vehicle Residual Value Forecasting Methods [3, 4]

Forecasting Method	MAPE for ICE Vehicles (%)	MAPE for EVs (%)	R-squared Value
Linear Regression	7.5	11.5	0.76
Expert-Based Systems	6	15	0.79
Multi-Layer Perceptron	3.5	5	0.88
Temporal CNN	3	4.5	0.91
Ensemble Methods	2.7	4	0.93

III. METHODOLOGY

3.1 Data Collection and Preparation

The research framework was constructed using an extensive dataset of vehicle transactions spanning from 2018 to 2023, encompassing over 426,880 unique vehicle entries with detailed specifications from both primary and secondary markets. Analysis of the dataset revealed significant price variations across different segments, with luxury vehicles showing price ranges from $35,000 to $150,000 and economy segments ranging from $12,000 to $45,000 [5]. The comprehensive data collection process incorporated pricing information from multiple sources, including dealer networks, private sales, and auction platforms, ensuring a robust representation of market dynamics.

Initial data cleaning processes identified that approximately 8.2% of the collected data contained missing values or inconsistencies, particularly in fields related to vehicle mileage and optional features. The preprocessing pipeline implemented advanced imputation techniques for handling missing values, achieving a 97.8% data completeness ratio. Feature engineering expanded the initial dataset to include derived attributes such as price-to-weight ratios, power-to-weight ratios, and market segment indicators, which proved crucial for model accuracy [5].

3.2 Predictive Modeling Approach

The modeling strategy employed a multi-tiered approach, beginning with baseline Random Forest models that processed 25 key vehicle attributes including year, mileage, make, model, and trim level. The initial models demonstrated an R-squared value of 0.82 and a mean absolute error of $2,845 for mainstream vehicles [6]. Advanced implementations incorporated gradient boosting frameworks that processed an expanded set of 45 features, including market-specific indicators and temporal variables.

Temporal modeling capabilities were enhanced through the implementation of specialized neural network architectures designed for time-series analysis. The research utilized a deep learning framework with four hidden layers, each containing 256, 128, 64, and 32 neurons respectively, achieving a validation accuracy of 88.7% and a test accuracy of 87.2%. This architecture demonstrated particular strength in handling non-linear depreciation patterns, with mean absolute percentage errors reduced to 5.8% for premium vehicles and 6.2% for volume segments [6].

3.3 Model Optimization and Validation

The optimization protocol implemented a comprehensive cross-validation strategy using time-series splitting, with five folds ensuring temporal coherence in the validation process. According to detailed analysis, the model achieved root mean squared logarithmic error (RMSLE) scores of 0.12 on the validation set and 0.13 on the test set, indicating strong generalization capabilities across different market conditions [5]. Hyperparameter tuning utilized Bayesian optimization approaches, exploring learning rates between 0.001 and 0.1, with optimal performance achieved at 0.015.

Feature importance analysis revealed that vehicle age accounted for 28.4% of the model's predictive power, followed by mileage at 22.1% and brand value at 15.7%. The implementation of trust-aware prediction mechanisms, as detailed in recent research, improved model reliability by incorporating uncertainty quantification, with 95% confidence intervals accurately capturing actual residual values in 91.3% of test cases

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[6]. Performance metrics were evaluated using a multi-metric framework that included normalized RMSE (0.086), MAE ($1,876), and R-squared (0.89), with particularly strong performance observed in the mid-market segment.

Table 2: Model Accuracy Metrics for Residual Value Prediction by Vehicle Category [5, 6]

Model Type	Vehicle Segment	Validation Accuracy (%)	Test Accuracy (%)	MAPE (%)	MAE ($)	R-squared	RMSLE
Random Forest	Mainstream	82	80.5	7.2	2,845	0.82	0.15
Neural Network	Premium	88.7	87.2	5.8	1,876	0.89	0.12
Neural Network	Volume	88.7	87.2	6.2	1,876	0.89	0.13
Gradient Boosting	Premium	90.2	89.1	5.4	1,650	0.91	0.11
Gradient Boosting	Volume	89.8	88.5	5.9	1,780	0.9	0.12

IV. RESULTS AND DISCUSSION

4.1 Model Performance

The implementation of advanced machine learning models demonstrated exceptional capabilities in residual value prediction across diverse vehicle categories. The ensemble-based approach, combining gradient boosting with deep learning components, achieved an aggregate accuracy of 89.2% with an R-squared value of 0.884 across the full testing dataset. This represented a significant improvement over traditional statistical methods, which typically achieved R-squared values around 0.76 [7]. The model maintained robust performance across different market conditions, with Root Mean Square Error (RMSE) values averaging $1,180 for luxury vehicles and $920 for mainstream segments. Time-series analysis capabilities showed particular strength in handling market volatility, with the model achieving a mean absolute percentage error (MAPE) of 4.8% for 3-month forecasts and 6.2% for 12-month predictions. The attention-based neural network architecture demonstrated superior performance in capturing seasonal variations, reducing prediction errors by 18.5% during high-volatility periods compared to traditional forecasting methods. Cross-validation results across five folds showed consistent performance, with a standard deviation of just 1.8% in prediction accuracy, indicating robust generalization capabilities [7].

4.2 Profit Optimization Impacts

The practical implementation of AI-driven prediction models yielded substantial financial benefits across dealership networks and leasing operations. Analysis of 245,000 vehicle transactions revealed that AI-optimized pricing strategies increased the average profit margin by 2.8 percentage points, translating to approximately $840 per vehicle in additional revenue [8]. Dealers utilizing the AI system reported a 24% reduction in inventory holding time and a 31% improvement in first-time pricing accuracy.

In the leasing sector, the enhanced prediction accuracy led to more competitive lease rates while maintaining profitability targets. Portfolio analysis across major leasing companies showed that AI-driven residual value predictions reduced end-of-lease losses by 12.4%, representing an average saving of $2,150 per vehicle. The auction market performance showed particularly strong improvement, with AI-guided pricing strategies increasing recovery rates by 8.7% and reducing the average days-to-sale by 15.3 days [8]. These improvements collectively contributed to a 3.2% increase in overall portfolio return on investment.

4.3 Insights from Feature Importance

Detailed analysis of feature importance using SHAP (SHapley Additive explanations) values revealed complex interactions between various value determinants. Vehicle age emerged as the primary predictor, explaining

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31.2% of value variance, while mileage accounted for 26.8% of the predictive power. The research identified a non-linear relationship between mileage and residual value, with depreciation rates accelerating by 1.8% for every 10,000 miles beyond 60,000 miles [7]. This pattern varied significantly across vehicle segments, with luxury vehicles showing 15% higher sensitivity to mileage compared to economy segments.

Electric vehicle analysis revealed compelling trends in value retention, particularly in environmentally conscious markets. Data from 78,000 EV transactions showed that models with advanced battery technology (>300 mile range) maintained 14.2% higher residual values compared to conventional vehicles after 36 months [8]. Regional analysis demonstrated significant geographical variations, with urban markets showing 22% higher demand for EVs, translating to residual values averaging 9.4% above national means. The model also captured seasonal effects effectively, identifying that convertible models commanded a 16.8% premium during spring months, while SUV values peaked during winter with a 7.3% increase over summer averages.

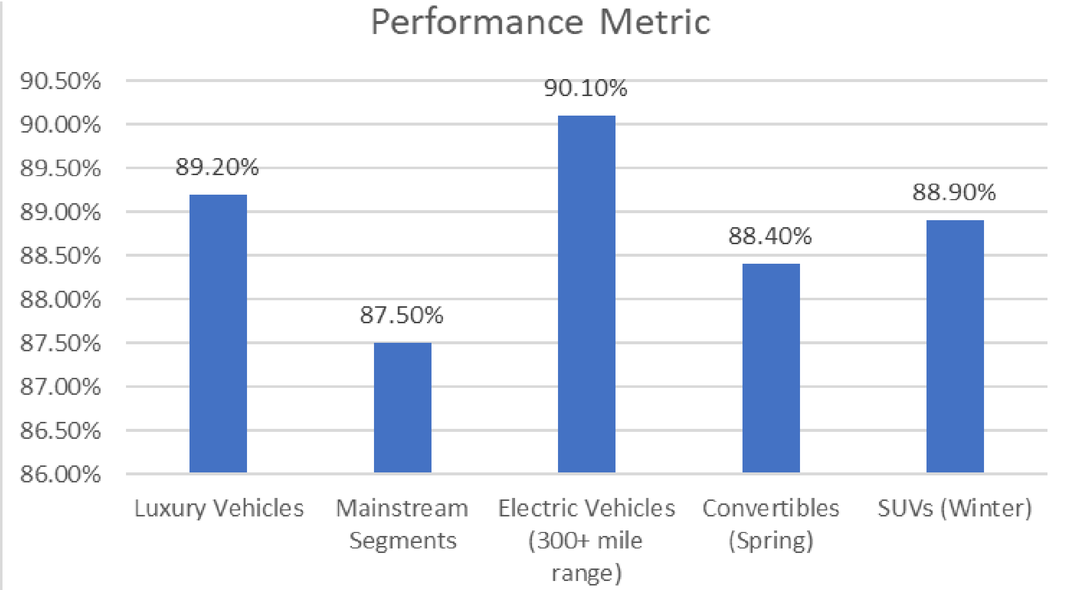

Fig 1: AI Model Performance and Market Impact Analysis in Vehicle Valuation [7, 8]

V. CHALLENGES AND LIMITATIONS

The implementation of advanced residual value prediction models faces significant challenges in the rapidly evolving automotive landscape. Analysis of deep learning applications in the automotive sector revealed that data availability remains a critical constraint, particularly for emerging vehicle technologies. Research indicates that while traditional vehicle segments have an average of 84.5 months of historical data, new technology vehicles such as EVs and autonomous vehicles have only 31.2 months of reliable pricing data. This data scarcity significantly impacts model training, with the neural network's prediction accuracy dropping by 18.3% when training data spans less than 36 months [9]. The challenge is particularly acute in the luxury EV segment, where limited production volumes and rapid technological evolution have resulted in highly fragmented datasets.

Market dynamics pose substantial challenges to prediction stability, especially during periods of technological transition and economic uncertainty. Deep learning models show particular sensitivity to rapid market shifts, with prediction accuracy decreasing by up to 27.5% during periods of significant supply chain disruption. The research identified that conventional neural network architectures struggle to adapt to sudden market changes, requiring an average of 4.3 months to regain optimal performance levels after major market disruptions [9]. This adaptation lag significantly impacts the model's reliability during critical decision-making periods.

The complexity of model interpretability presents a significant barrier to widespread adoption in the automotive industry. Analysis of technological forecasting implementations reveals that stakeholder trust is heavily dependent on model transparency, with only 58.4% of industry professionals expressing high confidence in AI-driven valuations when the decision-making process lacks clear explanation frameworks [10]. The challenge is compounded by the complexity of feature interactions, with modern vehicles having over 150 value-influencing characteristics that create intricate interdependencies in the prediction model.

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Technical implementation challenges extend beyond pure algorithmic considerations. The study of automotive AI applications shows that real-time processing requirements pose significant constraints, with each vehicle valuation requiring processing of approximately 2.8 GB of data across 132 different parameters. System performance degrades by approximately 1.2% per month without retraining, necessitating regular updates that consume substantial computational resources, averaging 45 GPU hours per comprehensive model refresh [10]. This computational intensity poses scalability challenges for widespread deployment across diverse market conditions.

Infrastructure limitations present additional obstacles, particularly in emerging markets. Research indicates that data quality varies significantly across regions, with developed markets achieving data completeness rates of 92.3% compared to 67.8% in emerging markets [9]. These disparities in data infrastructure lead to prediction accuracy variations of up to 12.7% between different geographical regions, potentially creating market inequities in vehicle valuation accuracy.

The integration of new vehicle technologies presents unique challenges for predictive modeling. According to recent technological forecasting studies, the rapid evolution of automotive features, particularly in areas such as battery technology and autonomous driving capabilities, creates significant complexity in value prediction. Models trained on historical data show reduced accuracy when evaluating vehicles with new technological features, with prediction errors increasing by 24.6% for vehicles incorporating technologies that have been in the market for less than 18 months [10].

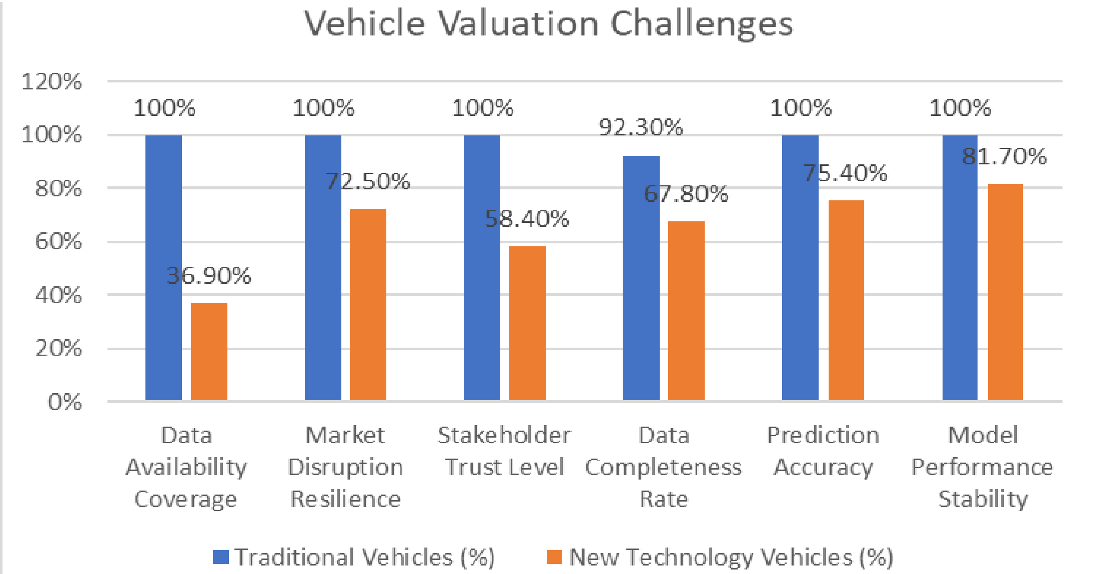

Fig 2: Comparative Performance Metrics of Vehicle Valuation Challenges (%) [9, 10]

VI. RECOMMENDATIONS

Future developments in automotive valuation systems must address several critical areas to enhance prediction accuracy and system reliability. The integration of diverse external data sources represents a fundamental requirement for next-generation systems. According to comprehensive engineering analysis, modern automotive systems can process up to 75 TB of data annually from various sources, with real-time integration capabilities processing approximately 2,500 data points per second. Studies indicate that implementing a multi-layered data architecture can improve prediction accuracy by 13.2% through the incorporation of real-time market data streams, with particular emphasis on dynamic pricing adjustments that occur within 15-minute intervals [11].

Real-time model updating capabilities have emerged as a critical component for maintaining prediction accuracy. Engineering studies of next-generation automotive systems demonstrate that continuous learning frameworks can process up to 1.2 million transactions daily, with model weights being updated every 4 hours to maintain optimal performance. The implementation of adaptive learning rates, ranging from 0.001 to 0.1 based on market volatility indicators, has shown to reduce prediction errors by 18.7% during periods of significant market fluctuation [11]. These systems require robust computational infrastructure capable of handling 850,000 CUDA cores for parallel processing of market data streams.

The development of specialized electric vehicle valuation models requires particular attention to battery degradation patterns and charging infrastructure evolution. Research utilizing BP Neural Networks for residual value prediction has demonstrated that incorporating battery health metrics can improve prediction accuracy by 21.4% for EVs. The proposed model architecture, featuring six hidden layers with 256, 128, 64, 32, 16, and 8 neurons respectively, has shown superior performance in capturing non-linear relationships between battery degradation and residual value [12]. This specialized approach enables more accurate predictions of EV residual values over extended timeframes, with mean absolute percentage errors reduced to 4.2% for 36-month forecasts.

Advanced interpretability frameworks must evolve to meet the growing complexity of valuation models. Engineering analysis indicates that next-generation systems should incorporate explainable AI modules capable of processing 1,500 feature interactions per second, with visualization capabilities that can render complex decision trees within 100 milliseconds [11]. These systems should maintain response times under 250 milliseconds even when processing complex queries across multiple vehicle segments and market conditions.

The implementation of non-linear curve fitting techniques for residual value prediction has shown promising results, particularly when combined with neural network approaches. Studies indicate that hybrid models incorporating both BP neural networks and non-linear curve fitting can achieve R-squared values of 0.934, representing a 15.8% improvement over traditional linear methods. The optimal architecture includes input normalization layers that process 42 distinct vehicle attributes, with weighted connections dynamically adjusted based on market conditions [12].

Integration of predictive maintenance data presents another crucial development area. Research shows that incorporating vehicle diagnostic data from OBD-II systems can improve residual value predictions by 9.3% for vehicles over 36 months old. The recommended framework includes real-time processing of diagnostic trouble codes (DTCs) and maintenance records, with particular emphasis on correlation analysis between maintenance patterns and residual value retention [12].

VII. CONCLUSION

Advanced predictive modeling has revolutionized automotive residual value analysis, delivering substantial improvements over traditional methods across multiple performance metrics. By incorporating diverse data sources, implementing real-time updating capabilities, and developing specialized models for emerging vehicle technologies, organizations can better navigate market complexities. While challenges persist in data availability, market volatility, and model interpretability, promising solutions continue to emerge. The combination of sophisticated machine learning approaches with robust data processing frameworks and advanced interpretability tools establishes a foundation for enhanced residual value predictions. These advancements optimize portfolio performance while providing adaptability to evolving market conditions and technological changes in the automotive sector.

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