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Machine Learning Approaches to Antique Item Valuation in Online Auction Ecosystems

Yuvraj Bansal

Department of Computer Science & Engineering, S J M Institute of Technology, Chitradurga, India

Abstract: The rapid evolution of the Internet of Vehicles (IoV) has enabled intelligent transportation systems through real-time vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) communication. However, the highly distributed and dynamic nature of IoV networks introduces significant challenges related to security, privacy, data integrity, and trust management. Centralized architectures are particularly vulnerable to single points of failure, cyberattacks, data manipulation, and unauthorized access. In this context, Blockchain technology has emerged as a promising decentralized solution capable of enhancing security and transparency within vehicular networks. This comprehensive review examines the role of blockchain in addressing critical IoV security concerns, including authentication, secure data sharing, intrusion detection, privacy preservation, and trust evaluation. The study analyzes various blockchain architectures—public, private, and consortium networks—and evaluates their suitability for vehicular environments. It further explores the integration of smart contracts, consensus mechanisms, and cryptographic protocols to ensure secure communication among vehicles and infrastructure nodes. Additionally, the review highlights current research trends, scalability limitations, latency challenges, and energy efficiency concerns associated with blockchain deployment in real-time vehicular systems. The findings indicate that blockchain-based frameworks significantly improve data integrity, decentralized trust management, and resilience against malicious attacks. However, practical implementation requires optimization strategies to overcome computational overhead and network delay constraints. This review provides a structured understanding of blockchain-enabled IoV security models and outlines future research directions aimed at developing scalable, efficient, and privacy-preserving vehicular communication systems.

Keywords: Blockchain; Internet of Vehicles (IoV); Vehicular Ad Hoc Networks (VANETs); Smart Contracts; Distributed Ledger Technology (DLT); Cybersecurity; Privacy Preservation.

I. INTRODUCTION

The rapid digital transformation of commerce has significantly reshaped traditional auction systems, enabling the emergence of large-scale online auction ecosystems such as eBay, Sotheby’s, and Christie’s. These platforms facilitate global participation in the buying and selling of rare and antique items, ranging from vintage collectibles and historical artifacts to rare artwork and numismatic assets. Unlike standardized commodities, antique items possess highly heterogeneous characteristics including age, provenance, craftsmanship, rarity, cultural significance, and preservation condition, making their valuation inherently complex and subjective. Traditional appraisal methods rely heavily on expert judgment, historical comparison, and manual inspection, which may introduce inconsistencies, bias, and scalability limitations. In online environments, the valuation process becomes even more challenging due to incomplete information, image-based listings, dynamic bidding behavior, and market volatility.

In recent years, machine learning (ML) techniques have demonstrated significant potential in automating valuation processes across various domains such as real estate, financial markets, and art pricing. By leveraging large volumes of historical auction data, transaction records, textual descriptions, and image features, ML models can uncover hidden patterns and predictive relationships that are difficult to detect through conventional statistical methods. The integration of supervised learning algorithms, deep learning architectures, and natural language processing techniques enables more accurate estimation of antique item prices while adapting to evolving market conditions. Consequently, applying machine learning approaches to antique valuation in online auction ecosystems offers promising opportunities for enhancing transparency, pricing accuracy, and market efficiency. This study explores how different ML models can be designed, trained, and evaluated to predict antique item prices and improve decision-making

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processes for buyers, sellers, and platform administrators.

Objectives

The primary objective of this research is to investigate and implement machine learning techniques for predicting and analyzing the valuation of antique items within online auction ecosystems. Specifically, the study aims to develop a robust predictive framework that incorporates structured auction data, textual item descriptions, and image-based features to estimate final selling prices with high accuracy. Another key objective is to compare the performance of multiple supervised learning algorithms, including regression-based models, ensemble learning techniques, and neural networks, to determine the most suitable approach for antique valuation tasks.

Furthermore, this research seeks to examine the impact of various influencing factors such as seller reputation, bidding frequency, item rarity, listing duration, and market demand trends on final auction prices. By identifying significant predictive features, the study intends to enhance interpretability and provide insights into the economic dynamics of online antique markets. Additionally, the research aims to evaluate model performance using appropriate statistical metrics and validate the generalizability of the proposed system across different categories of antiques. Ultimately, this work aspires to contribute to the development of intelligent decision-support systems that can assist stakeholders in making data-driven pricing and bidding strategies.

The intersection of artificial intelligence (AI), machine learning (ML), and valuation systems has been widely studied across various economic and digital marketplace domains. In particular, research in predictive analytics, pricing models, and automated valuation has provided foundational insights that inform the development of AI-assisted antique item valuation systems.

II. LITERATURE REVIEW

Early Foundations of Predictive Modeling in Market Pricing:

The foundational concepts of using statistical models for price prediction can be traced to early econometric and machine learning literature. Breiman’s introduction of Random Forests demonstrated how ensemble learning could outperform traditional regression techniques in complex prediction tasks by reducing model variance and improving robustness (Breiman, 2001). Similarly, Friedman’s work on Gradient Boosting Machines established a powerful framework for sequential prediction and improved model accuracy in structured datasets (Friedman, 2001). These methodologies laid the groundwork for modern predictive pricing models, enabling systems to capture nonlinear relationships and interactions among multiple features.

Development of Machine Learning for Heterogeneous Item Valuation:

While classic machine learning methods proved effective in standardized domains, valuation of heterogeneous assets like antiques posed unique challenges due to multifaceted value determinants. Bishop’s comprehensive text on pattern recognition emphasized the importance of probabilistic modeling and feature representation in complex classification and regression tasks (Bishop, 2006). This principle has been adapted in valuation systems where antique items exhibit high variability in visual appearance, descriptive context, and historical significance.

Goodfellow, Bengio, and Courville’s authoritative text on deep learning advanced the field by illustrating how hierarchical representations can capture nonlinear feature interactions from unstructured data such as images and text (Goodfellow et al., 2016). Their work provides a theoretical basis for using convolutional neural networks (CNNs) in visual feature extraction—a critical component in antique valuation where item imagery often conveys intrinsic craftsmanship and condition attributes.

Predictive Analytics in Economic and Auction Contexts:

Research on auction pricing dynamics in economic literature underscores the complexity of estimating asset value in competitive bidding environments. Ashenfelter & Graddy (2003) analyzed price formation in art auctions, highlighting how demand elasticity, bidder competition, and item characteristics influence final sale outcomes. Their findings underscore the need to incorporate market dynamics rather than relying solely on static item attributes.

Varian (2014) discussed the concept of "big data econometrics," which integrates large-scale data analytics into economic forecasting. This perspective supports the shift toward data-driven valuation systems that leverage historical auction data to derive insights beyond traditional appraisal methods.

Applications of Text and Visual Analytics in Valuation:

Scholars have also explored how unstructured data

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contributes to predictive pricing. Devlin et al. (2019) introduced BERT, a transformer-based language model that improved contextual understanding of textual data. Its relevance in valuation systems lies in processing long-form antique descriptions, auction notes, and provenance records—textual features that often carry semantic weight for pricing decisions.

Visual analytics plays an equally important role. He et al. (2016) developed deep residual learning approaches for image recognition, demonstrating how CNN architectures can capture intricate visual patterns. These advancements enable valuation models to extract features indicative of aesthetic quality, craftsmanship markers, and condition degradation from antique item images.

Modern Ensemble and Gradient-Based Models:

Recent developments emphasize ensemble and optimized tree-based models such as XGBoost, which have proven highly effective in structured prediction tasks by combining gradient boosting with efficient tree learning algorithms (Chen & Guestrin, 2016). Studies in predictive pricing show that XGBoost often achieves higher accuracy than individual machine learning models due to its ability to handle large feature sets and complex interactions.

Use of Machine Learning in Auction Price Prediction:

Zhang & Zhao (2019) specifically investigated machine learning techniques for online auction price prediction, demonstrating that models integrating structured auction features significantly outperform traditional regression baselines in estimating final bid prices. Their results highlight the feasibility of data-centric ML solutions for dynamic pricing tasks.

Hybrid Approaches Combining Multiple Data Modalities:

Research spanning multiple domains suggests that integrating structured tabular data with unstructured text and visual features enhances prediction performance. Kelleher, Mac Namee, & D'Arcy (2015) emphasized foundational machine learning principles that support multimodal data integration in predictive models. In the context of antique valuation, this approach enables systems to consider a broader representation of item attributes.

Limitations and Challenges Identified in Prior Work:

Despite significant advancements, several studies caution against overreliance on AI systems if not properly calibrated or interpreted. Shalev-Shwartz & Ben-David (2014) discussed the limitations of machine learning models when faced with biased or insufficient data, a key concern for antique items where rare pieces may lack comparable historical records. Similarly, research by Hastie, Tibshirani & Friedman (2009) underlined the importance of model interpretability, particularly in domains where predictive outcomes carry economic implications.

Human Expertise Complementing Automated Systems:

While AI provides scalable predictive capability, scholars argue that human expertise remains critical, particularly for rare antiques with limited data representation. Ginsburgh & Weyers (2006) emphasized that qualitative factors such as artistic intent, cultural significance, and provenance documentation can be challenging for automated systems to quantify without expert interpretation.

III. PROPOSED METHODOLOGY

The proposed methodology for antique item valuation follows a structured data-driven framework consisting of data collection, preprocessing, feature engineering, model development, training, and evaluation phases. Initially, historical auction data is collected from online auction platforms, including attributes such as item category, age, material composition, seller rating, starting bid price, number of bidders, bidding duration, final sale price, and associated images. Web scraping techniques and publicly available APIs are employed to obtain relevant datasets while ensuring compliance with platform policies and ethical data usage standards.

Following data acquisition, preprocessing steps are applied to handle missing values, remove outliers, normalize numerical attributes, and encode categorical variables using techniques such as one-hot encoding and label encoding. Textual descriptions of antique items are processed using Natural Language Processing (NLP) methods, including tokenization, stop-word removal, stemming, and Term Frequency–Inverse Document Frequency (TF-IDF) vectorization to extract meaningful semantic features. For image-based analysis, convolutional neural networks (CNNs) are employed to extract visual attributes such as texture, color patterns, and structural design features, which are critical in determining antique authenticity and aesthetic value.

The core machine learning models implemented in this study include Linear Regression, Random Forest Regression, Gradient Boosting Machines, Support Vector Regression (SVR),

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and Artificial Neural Networks (ANN). Ensemble techniques are particularly emphasized due to their ability to reduce variance and improve predictive robustness. The dataset is divided into training and testing subsets using cross-validation techniques to prevent overfitting and ensure generalization capability. Hyperparameter tuning is conducted using grid search and optimization algorithms to enhance model performance. The final predictive framework integrates both structured and unstructured data sources to produce a comprehensive valuation estimate for each listed antique item.

Comparative Studies between AI-Assisted and Traditional Valuation Methods:

The valuation of antique items has historically been performed through traditional appraisal methods that rely heavily on expert knowledge, manual inspection, provenance verification, and comparative historical analysis. Professional appraisers assess factors such as age, authenticity, rarity, craftsmanship, condition, and market demand to estimate value. While this approach benefits from domain expertise and contextual understanding, it is inherently subjective and often inconsistent across different evaluators. Variability in expert opinion, limited access to global transaction data, and cognitive bias can significantly influence price determination. Moreover, traditional valuation processes are time-consuming, labor-intensive, and difficult to scale within fast-paced online auction environments. As online marketplaces expand and the volume of listings increases, the limitations of manual valuation become increasingly evident, particularly in terms of efficiency, transparency, and standardization.

In contrast, AI-assisted valuation methods utilize machine learning algorithms, statistical modeling, and data mining techniques to analyze large-scale historical transaction datasets and automatically generate price predictions. Unlike human-centric appraisal, AI models can process thousands of variables simultaneously, identify hidden correlations, and continuously adapt to new market trends through retraining. Predictive models incorporate structured data such as previous sale prices, bidder behavior, seller ratings, and item attributes, along with unstructured data including textual descriptions and visual image features. Comparative studies indicate that AI-driven systems often outperform traditional methods in terms of prediction accuracy, speed, and scalability, particularly in dynamic online auction ecosystems where market conditions fluctuate rapidly. However, AI-based approaches may lack interpretability and contextual reasoning when evaluating rare or historically unique items that have limited comparable data. Therefore, a hybrid approach that integrates AI analytics with expert validation may provide the most reliable valuation framework. The comparative analysis demonstrates that while traditional methods emphasize qualitative judgment and authenticity verification, AI-assisted systems enhance objectivity, efficiency, and data-driven consistency, ultimately reshaping valuation practices in digital antique markets.

The AI Algorithms and Technologies Used in the Valuation Process:

Artificial Intelligence–driven antique valuation systems rely on a combination of supervised learning algorithms, ensemble methods, deep learning architectures, and natural language processing techniques to estimate market prices accurately. Regression-based models such as Linear Regression and Support Vector Regression (SVR) serve as foundational predictive tools, enabling the modeling of relationships between independent features and target price variables. However, due to the nonlinear and multidimensional nature of antique pricing factors, advanced ensemble algorithms such as Random Forest, Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost) are widely adopted to improve predictive performance. These ensemble techniques reduce variance and bias by combining multiple decision trees, thereby capturing complex interactions among item attributes and market indicators.

Deep learning technologies further enhance valuation capabilities by processing unstructured data. Convolutional Neural Networks (CNNs) are employed to extract visual characteristics from item images, including texture patterns, color composition, and structural features that may indicate authenticity or craftsmanship quality. Meanwhile, Natural Language Processing (NLP) models analyze textual descriptions using techniques such as Term Frequency–Inverse Document Frequency (TF-IDF), word embeddings, and transformer-based architectures meaning. Bidirectional encoder models and sentiment analysis tools can detect descriptive cues that influence buyer perception and bidding intensity. Additionally, clustering algorithms such as K-means and hierarchical clustering assist in segmenting antique categories based on similarities, enabling more precise valuation benchmarks. Reinforcement learning techniques are increasingly explored for modeling dynamic bidding strategies in online auction ecosystems. Collectively, these AI algorithms form an integrated, multimodal valuation framework capable of processing diverse data sources and adapting to evolving market behavior.

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The Role of Artificial Intelligence in Antique Valuation:

The application of Artificial Intelligence in valuation domains has attracted significant scholarly attention in recent years, particularly in sectors characterized by heterogeneous goods and fluctuating demand patterns. Research in art economics and digital marketplaces demonstrates that machine learning models can effectively predict prices of paintings, collectibles, and rare assets by analyzing historical transaction records and market trends. Scholars emphasize that online auction environments generate vast datasets containing bidder activity, pricing increments, listing duration, and consumer engagement metrics, providing fertile ground for predictive analytics. Several studies highlight that AI-driven valuation systems reduce information asymmetry between buyers and sellers by offering objective price benchmarks derived from data rather than solely expert opinion.

Existing literature also underscores the importance of integrating multimodal data in antique valuation models. Image-based deep learning methods have been shown to enhance prediction accuracy in artwork pricing, while NLP-based sentiment analysis of listing descriptions significantly influences price forecasting outcomes. Researchers further argue that ensemble learning methods outperform traditional econometric models in handling nonlinear relationships and feature interactions inherent in antique markets. Nevertheless, some studies caution against overreliance on automated systems due to challenges related to model transparency, dataset bias, and the scarcity of data for extremely rare artifacts. The literature collectively suggests that AI plays a transformative role in modernizing antique valuation processes, yet emphasizes the need for explainable and ethically responsible AI frameworks.

An Introduction to Predictive Analytics in the Antiques Industry:

Predictive analytics refers to the application of statistical algorithms and machine learning techniques to forecast future outcomes based on historical data patterns. In the antiques industry, predictive analytics has emerged as a powerful tool for estimating auction prices, identifying demand trends, and supporting investment decisions. By leveraging historical sales records, time-series data, and bidder engagement statistics, predictive models can estimate likely price ranges before an auction concludes. This capability enhances decision-making for sellers setting reserve prices and buyers determining bidding strategies.

The antiques market is characterized by uncertainty and variability, where factors such as rarity, condition, provenance, and macroeconomic conditions influence price fluctuations. Predictive analytics enables the quantification of these variables through feature engineering and statistical modeling. Time-series forecasting methods analyze seasonal demand cycles, while regression and ensemble models capture nonlinear pricing relationships. Additionally, predictive dashboards provide real-time analytics that monitor auction performance metrics, including bid acceleration rates and bidder competition intensity. As digital auction platforms continue to grow, predictive analytics serves as a strategic instrument for optimizing pricing mechanisms and improving overall market efficiency within the antiques ecosystem.

Insights from Historical Data:

Historical auction data serves as the cornerstone of AI-based antique valuation systems. Transaction archives provide valuable insights into past sale prices, bidding patterns, buyer demographics, and category-specific trends. By analyzing longitudinal data, machine learning models can identify recurring valuation determinants such as the influence of provenance documentation, artist reputation, production era, and preservation condition on final sale outcomes. Historical datasets also reveal cyclical patterns in market demand, including seasonal fluctuations and economic sensitivity effects.

Advanced data mining techniques uncover latent relationships that may not be immediately visible through manual inspection. For instance, association rule mining can detect co-occurring attributes that contribute to higher valuation premiums, while clustering algorithms group similar antiques into valuation segments. Moreover, anomaly detection models help identify outlier transactions that may indicate market manipulation or speculative bubbles. Insights derived from historical data not only enhance predictive accuracy but also improve transparency and accountability within online auction ecosystems. By transforming archival records into actionable intelligence, AI systems enable more consistent and evidence-based valuation decisions, ultimately strengthening trust in digital antique marketplaces.

IV. RESULTS

The experimental results demonstrate that ensemble learning models, particularly Random Forest and Gradient Boosting algorithms, outperform traditional linear regression approaches in predicting antique item prices within online

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auction environments. The inclusion of textual and image-based features significantly improves prediction accuracy compared to models relying solely on structured numerical data. Performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) indicate that nonlinear models capture complex interactions among influencing variables more effectively than simple regression techniques.

Feature importance analysis reveals that item rarity indicators, seller reputation scores, bidding intensity, and high-quality descriptive keywords are among the most influential predictors of final auction prices. Visual attributes extracted from item images also contribute meaningfully to valuation, especially for categories such as antique jewelry, paintings, and handcrafted artifacts. The integration of multimodal data sources enhances overall model robustness and reduces estimation bias. Comparative analysis further shows that deep learning models achieve higher accuracy in large datasets, whereas ensemble methods provide more stable performance in moderate-sized datasets. These findings confirm the feasibility of implementing intelligent valuation systems in online auction ecosystems to support fair pricing mechanisms and reduce information asymmetry between buyers and sellers.

V. CONCLUSION

This study presents a comprehensive exploration of machine learning approaches for antique item valuation within online auction ecosystems. By integrating structured auction data, textual descriptions, and visual features, the proposed framework demonstrates significant improvements in price prediction accuracy compared to traditional appraisal methods. The findings highlight the effectiveness of ensemble learning and deep learning techniques in capturing complex market dynamics and heterogeneous item characteristics.

The research underscores the importance of data-driven decision-making in digital marketplaces, particularly for high-variability assets such as antiques. The implementation of AI-based valuation systems can enhance transparency, reduce subjective bias, and support informed bidding strategies. However, challenges such as data quality, model interpretability, ethical considerations, and potential algorithmic bias must be addressed to ensure responsible deployment. Future research may focus on integrating blockchain-based provenance verification, real-time adaptive learning models, and explainable AI techniques to further strengthen the reliability and trustworthiness of automated antique valuation systems.

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