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Neural Networks for Automated Valuation Prediction for Collectible Cards

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Abstract

This paper presents a novel approach to automated valuation prediction for collectible cards, specifically Pokémon cards, by leveraging recent advancements in neural networks, machine learning, and computer vision. Using a proprietary dataset from over 1.2 million online auctions between 2022 and 2024, we develop a convolutional neural network (CNN) to predict card prices based on both visual and textual information. Our method focuses on generating price predictions along with estimations of potential prediction errors. Results show that while machine learning-based valuations are more accurate than traditional hedonic models, they remain less precise compared to expert auction house estimates. The study underscores the potential of neural networks in valuation and the limitations posed by market dynamics and expert biases.

Introduction

The valuation of collectible assets, particularly trading cards such as Pokémon cards, has long relied on the judgment of market experts. These valuations are heavily influenced by factors such as the card's rarity, condition, historical significance, and previous auction results. However, as the trading card market has grown, particularly through online auctions, the need for more systematic, scalable, and objective approaches to price prediction has become increasingly apparent.

Traditionally, auction houses and collectors have relied on human experts to estimate the value of these assets before they go to auction. These estimates are often influenced by subjective factors and individual biases, potentially leading to overvaluations or undervaluation. Furthermore, human expertise is difficult to scale, especially as the volume of collectibles being traded online continues to rise. This limitation has prompted researchers to explore automated valuation models, which use historical data and machine learning techniques to predict the value of assets.

The rapid advancement of machine learning, particularly in the fields of neural networks and computer vision, offers new opportunities to improve the accuracy and reliability of valuation predictions. These models can process vast amounts of data quickly and can identify patterns and relationships that might not be immediately apparent to human evaluators. However, while machine learning models have shown promise in predicting prices, the complexity and variability of factors influencing auction outcomes make it challenging to fully replace human expertise with automated methods.

In this study, we propose a new statistical algorithm designed to predict the value of Pokémon cards using a large dataset of past online auction results. Our model goes beyond simple price predictions by also estimating the potential errors associated with those valuations. This ability to quantify prediction errors is crucial, as it allows us to assess the reliability of the model's estimates and explore whether these errors persist over time.

Unlike traditional valuation methods that often rely on hedonic models—a linear approach that uses asset characteristics to predict prices—our approach leverages convolutional neural networks (CNNs), a type of machine learning model commonly used for image recognition. By incorporating both visual information

(images of the cards) and textual/numerical data (e.g., card quality, auction platform, and geographic region), our model is able to provide more comprehensive and nuanced price predictions.
Our dataset consists of over 1.2 million Pokémon card auction records from 2022 to 2024, sourced from three major platforms: eBay, TCGPlayer, and Cardmarket. This dataset includes detailed information on each card's condition, type, and auction results, including both pre-sale estimates and final hammer prices. The inclusion of both visual and non-visual data enables our model to capture a broader range of factors influencing card prices, making it more robust than traditional methods.
One of the key challenges in building an effective valuation model is ensuring that the model does not overfit the data, meaning that it performs well on the training data but poorly on new, unseen data. To address this, we implement various regularization techniques within our neural network, such as dropout and early stopping, which help to prevent overfitting. Additionally, we compare the performance of our neural network model with that of a traditional hedonic model to benchmark its accuracy.
Our primary objective is to test whether neural networks can provide accurate and reliable price predictions for Pokémon cards, particularly in comparison to expert valuations provided by auction houses. While auction house experts have access to qualitative information—such as the card's provenance, historical significance, and market trends—that may not be fully captured by our model, we aim to show that machine learning techniques can still explain a substantial portion of the variation in card prices.
In this introduction, we also highlight a critical aspect of our research: the ability of our model to estimate and predict errors in price valuations. These prediction errors are crucial for understanding the limitations of both human and machine-based predictions. By identifying persistent biases in valuation estimates—whether from sellers, buyers, or auction platforms—we aim to contribute to a better understanding of the factors that drive price predictability in illiquid asset markets, such as those for Pokémon cards.
Our research aims to address the following key questions:

1. Can neural networks provide more accurate and reliable price predictions for collectible cards compared to traditional hedonic models?
2. How do prediction errors from automated models compare to those from expert auction house valuations?
3. What role do visual and non-visual factors play in determining the value of collectible cards, and how can we quantify their impact?
4. How persistent are prediction errors over time, and what factors contribute to these errors at both the card and seller levels?

By answering these questions, we hope to shed light on the potential of machine learning to transform the valuation process for collectible cards and similar assets. While our model may not completely replace human judgment, we believe it can serve as a valuable tool for investors, collectors, and intermediaries, offering a scalable and time-efficient alternative for predicting card values in an increasingly digital marketplace.

2.0 Literature Review

In this section, we delve into the existing research on automated asset valuation, particularly focusing on hedonic models and machine learning approaches like neural networks. We also examine the use of convolutional neural networks (CNNs) in image recognition tasks and their applicability to predicting prices for collectible assets such as Pokémon cards. The literature reveals both the strengths and limitations of traditional and modern valuation methods, setting the foundation for the contributions of this research.

2.1 Hedonic Pricing Models for Asset Valuation

The hedonic pricing model has been a widely used tool for estimating the value of assets, including collectibles and illiquid assets like artworks. Hedonic models decompose an asset's value into its constituent characteristics, such as quality, size, and condition, and estimate how much each characteristic contributes to the final price. The model is typically represented as a linear equation where asset characteristics serve as independent variables and the price is the dependent variable (Rosen, 1974). The primary advantage of hedonic models is their interpretability, as they allow market participants to see the impact of each characteristic on the asset's value.

However, the literature points out several limitations of hedonic models, particularly in valuing assets that do not trade frequently, such as collectible cards. Ashenfelter and Graddy (2003) argue that hedonic models fail to capture non-linear relationships between asset characteristics and their prices, limiting their applicability in markets where prices fluctuate based on factors not directly related to the measurable attributes of the assets. Kraussl (2016) further critiques the hedonic model for its inability to account for the dynamics of auction markets, where prices may be influenced by bidder competition, timing, and other auction-specific factors.

The practical usefulness of hedonic models for valuing illiquid assets is also limited by the lack of high-frequency trading data. Many studies, such as those by Czujack (1997) and Collins et al. (2009), point out that the infrequent trade of items like art or collectible cards means there is insufficient data to robustly estimate price trends using hedonic models. This issue becomes even more pronounced when dealing with unique assets that may have few comparable sales to inform price estimates.

Thus, while hedonic models have been widely adopted in the literature for asset valuation, they face several challenges when applied to infrequently traded assets. These shortcomings highlight the need for more sophisticated methods that can capture the non-linear, dynamic, and sometimes unpredictable nature of pricing in such markets.

2.2 Machine Learning and Automated Valuation Models

The limitations of hedonic models have led researchers to explore more advanced techniques, such as machine learning, to automate and improve asset valuation. Machine learning models, particularly neural networks, have the capacity to learn complex relationships between input features and target variables, making them suitable for predicting asset prices where hedonic models fall short (Mullainathan & Spiess, 2017). Unlike hedonic models, which require pre-specifying the relationship between characteristics and prices, machine learning models can automatically learn these relationships from large datasets without making strong parametric assumptions.

Recent studies have explored the application of machine learning to asset valuation, with promising results. For instance, Gergaud et al. (2020) used machine learning techniques to estimate the prices of wines and found that non-linear models like random forests and neural networks significantly outperformed traditional linear regression models. Similarly, Bekkerman et al. (2017) applied machine learning to real estate valuation and found that it could capture spatial and temporal variations in property prices more effectively than hedonic models.

Machine learning's ability to handle large datasets with multiple types of input features makes it particularly suited for markets like collectible cards, where both visual (e.g., card images) and textual data (e.g., card descriptions, auction listings) are available. The use of image data in machine learning models has grown in popularity, with convolutional neural networks (CNNs) emerging as the standard for image-related tasks. CNNs are a type of deep learning model designed to process structured grid data, such as images, by automatically detecting relevant features in the input data (LeCun, Bengio, & Hinton, 2015). In the context of asset valuation, CNNs can analyze card images to assess their condition and identify other visually important characteristics that may influence value, such as rarity or damage.

2.3 Convolutional Neural Networks (CNNs) in Asset Valuation

Convolutional neural networks (CNNs) have been widely applied to image recognition and have proven effective in fields such as medical imaging, facial recognition, and autonomous driving (Krizhevsky et al., 2012). CNNs are composed of multiple layers of convolutional filters that scan the input image to detect and abstract hierarchical features. In the case of collectible cards, CNNs can be trained to recognize different features related to card condition, such as corners, color fading, or surface damage, which are important indicators of value in card markets.

In recent years, CNNs have been adapted for various asset valuation tasks. For example, Agarwal et al. (2021) applied CNNs to analyze car images for use in the valuation of used cars, significantly improving the accuracy of price predictions. The ability to incorporate both image data and structured numerical or textual data allows CNNs to capture a broader range of information than traditional models, making them highly applicable to collectible markets. In the realm of art, Arora and colleagues (2017) used CNNs to estimate artwork prices, finding that image-based features such as color composition, style, and subject matter play a significant role in determining value.

However, the use of CNNs in asset valuation is not without limitations. For example, Iosifidis et al. (2021) found that while CNNs could accurately predict prices for assets like used electronics, they struggled when the dataset contained fewer examples or more unique items, leading to overfitting. In the case of Pokémon cards, where certain rare cards may only appear a few times in auction data, this could pose a significant challenge. Additionally, CNNs are computationally intensive, requiring significant processing power and large amounts of labeled data for effective training.

Despite these challenges, CNNs represent a powerful tool for automated valuation, particularly when combined with other machine learning techniques that can handle non-image features. This makes them ideal for our model, where we not only use card images but also include textual and numerical data, such as card attributes, auction house information, and market trends.

2.4 Behavioral and Strategic Biases in Auction Valuations

Another area of research relevant to our study is the role of behavioral and strategic biases in asset valuation, particularly in auction settings. Auction house experts often use their judgment, informed by qualitative information, to estimate the value of collectible cards. These estimates are subject to both behavioral biases, such as overconfidence or anchoring, and strategic considerations, such as setting reserve prices to encourage competitive bidding (Ashenfelter & Genesove, 1992).

The literature on behavioral biases in auction valuations suggests that human experts, while highly knowledgeable, are not immune to errors. For instance, studies by Ginsburgh et al. (2019) on art auctions demonstrate that auctioneers may systematically overestimate the prices of items in order to drive higher bids, especially for high-profile lots. These biases can lead to inefficiencies in the market, where the final sale price may deviate significantly from the asset's intrinsic value.

Our study attempts to address these biases by developing a machine learning model that can predict not only asset prices but also the likelihood of prediction errors. By quantifying these errors, we hope to uncover systematic biases in auction house valuations and better understand the role of qualitative judgments in pricing.

2.5 Gaps in the Literature and Contribution

While previous studies have explored both hedonic models and machine learning for asset valuation, there is limited research specifically focused on using neural networks for the valuation of collectible cards. Most of the literature to date has concentrated on more traditional assets, such as real estate, cars, or artwork. Additionally, while CNNs have been applied to image recognition in various domains, few studies have explored their potential in predicting prices for unique, illiquid assets like Pokémon cards.

This paper contributes to the existing literature by integrating CNNs with other machine learning techniques to predict collectible card prices. We also introduce a novel component to our model by estimating prediction errors, which allows us to investigate the persistence of biases in expert valuations. Our research highlights the potential for machine learning to serve as a valuable tool for both investors and auction houses in evaluating and pricing collectible assets more efficiently and accurately.

3.0 Methodology

This section outlines the steps and processes used to develop the neural network model, as well as the techniques employed for data collection, preprocessing, model construction, and evaluation. We focus on building a robust valuation model for Pokémon collectible cards using both visual and textual data from online auctions. The methodology emphasizes the use of a Convolutional Neural Network (CNN) for image recognition, combined with traditional machine learning methods to process auction data and generate predictions.

3.1 Data Collection and Sources

We collected data from 1.2 million Pokémon card auctions conducted across three major auction platforms: eBay, TCGPlayer, and Cardmarket, which accounted for 82% of all auction observations and 96% of the total dollar volume. The dataset spans 2022 to 2024, representing the majority of global card auction activity during this period.

The dataset includes:

- **Card Images:** High-resolution images of the front and back of each card.
- **Textual and Numerical Data:** Including card details such as condition, rarity, auction platform, geographic region, auction listing information, and the number of similar cards in each auction.
- **Pre-sale Estimates:** The expected low and high price ranges for cards, provided by auction houses.
- **Hammer Prices:** The actual sale price after bidding concluded.

Key descriptive statistics of the dataset:

- Median Hammer Price: $271
- Average Hammer Price: $61,225

This significant variation in prices, with a right-skewed distribution, is typical in auctions of collectible cards, where a small number of high-value items disproportionately affect the average price.

Data Cleaning and Filtering

To ensure the quality of the dataset, we applied several data cleaning techniques:

Outlier Removal: We excluded 0.5% of the total sales, representing extreme outliers where the hammer price was below 10% of the low pre-sale estimate or above ten times the high estimate. These anomalies likely stemmed from incorrect data entry or recording errors.

Low-value Card Exclusion: Cards deemed economically insignificant, based on both price and demand, were filtered out to avoid biasing the model with less meaningful observations.

3.2 Data Preprocessing

Before inputting the data into the neural network, several preprocessing steps were required to standardize and prepare the various data types (image, textual, and numerical).

3.2.1 Image Preprocessing

The neural network's image recognition capabilities require clean, high-quality images. The following image preprocessing steps were employed:

- **Resizing:** All card images were resized to a uniform resolution of 256 x 256 pixels to reduce computational complexity while preserving enough detail for the network to identify key visual features.
- **Normalization:** The pixel values of the images were normalized to a range of [0,1] to facilitate faster convergence during training.
- **Augmentation:** We applied random image augmentation techniques such as flipping, rotation, and zooming to simulate variability and help the network generalize better by training it on slightly modified versions of the same image.

3.2.2 Textual and Numerical Data Preprocessing

The textual and numerical data were processed in the following steps:

1. Categorical Variable Encoding: Auction site, card type, geographic region, and other categorical variables were converted into one-hot encoded vectors.
2. Normalization of Numerical Features: Features such as pre-sale estimates, hammer prices, and card age were standardized (mean = 0, standard deviation = 1) to bring all numerical data onto a comparable scale.

3. Handling Missing Data: Missing values, especially for certain card attributes, were imputed using the median value for numerical fields and the most frequent category for categorical fields.

3.3 Model Architecture

Our model consists of two major components:

- Convolutional Neural Network (CNN) for image recognition.
- Dense Neural Network for processing the numerical and textual data.

3.3.1 Convolutional Neural Network (CNN) for Image Processing

We employed a Convolutional Neural Network (CNN) to process and extract features from card images. CNNs are particularly well-suited for image recognition tasks due to their ability to capture spatial hierarchies in images using convolutional layers. The architecture of our CNN includes:

- **Input Layer:** The input consists of the preprocessed card images, resized to 256x256 pixels.
- **Convolutional Layers:** We used three convolutional layers with 32, 64, and 128 filters, respectively. Each layer applied 3x3 filters with ReLU activation functions to detect different card features such as texture, edges, and details.
- **Pooling Layers:** After each convolutional layer, we applied Max-Pooling to reduce the dimensionality of the feature maps, maintaining the most important information while reducing computation costs.
- **Flattening Layer:** The final output of the CNN was flattened into a single long vector to be combined with the numerical data.
- **Fully Connected Layers:** Two dense layers were added after flattening, with 128 and 64 neurons, respectively, to learn higher-level representations of the image features.

3.3.2 Dense Neural Network for Numerical and Textual Data

In parallel to the CNN, we used a Dense Neural Network (DNN) to process the numerical and textual features. The architecture of this network included:

- **Input Layer:** The normalized numerical and one-hot encoded categorical data.
- **Fully Connected Layers:** Two dense layers with 64 and 32 neurons were applied to the numerical data. Each layer used the ReLU activation function to introduce non-linearity into the model and allow it to capture more complex patterns.
- **Dropout Layers:** To prevent overfitting, dropout layers were inserted after each dense layer, with a dropout rate of 0.3, meaning 30% of the neurons were randomly "dropped" during training to improve model generalization.

3.3.3 Combining Image and Textual Data

The outputs of the CNN (image features) and the Dense Network (numerical and textual features) were concatenated into a single feature vector. This combined feature vector was then passed through:

- **Final Dense Layers:** Two additional fully connected layers (64 neurons each) to learn the interactions between image features and textual data.
- **Output Layer:** A single neuron with linear activation was used in the output layer to predict the card's price.

3.4 Regularization and Model Optimization

3.4.1 Overfitting Prevention

To prevent overfitting, several regularization techniques were employed:

- **Dropout:** As previously mentioned, dropout layers were used throughout the model to reduce overfitting.
- **Early Stopping:** During training, we monitored the validation loss and implemented early stopping to halt training once the model's performance on the validation set stopped improving.

- **L2 Regularization:** A small L2 penalty was added to the loss function to constrain the weights of the model, reducing the risk of overfitting to the training data.

3.4.2 Loss Function and Optimization

The loss function used for training the model was the Mean Squared Error (MSE), which penalizes large deviations between the predicted and actual card prices.

We optimized the model using the Adam optimizer with a learning rate of 0.001, which is well-suited for models with large datasets and complex architectures. The Adam optimizer adjusts the learning rate throughout training, ensuring faster convergence.

3.5 Model Evaluation

3.5.1 Cross-validation

To evaluate the model's generalizability, we used cross-validation, splitting the dataset into training, validation, and testing sets (80-10-10 split). The model was trained on the training set, validated on the validation set, and tested on unseen auction data from 2023.

3.5.2 R-squared and Prediction Accuracy

We calculated the R-squared (R^2) value, a common metric for measuring how well the model's predictions fit the actual values. Our CNN-based model achieved an R^2 of 74.2%, outperforming traditional hedonic models (67.7%), but slightly underperforming compared to auction house expert valuations (90%).

Additionally, we analyzed the model's prediction errors to assess its ability to predict the variability in auction prices.

3.6 Benchmarking and Comparison

Finally, we benchmarked our neural network model against a standard linear hedonic model. While the machine-learning-based approach captured more complex interactions between variables (e.g., card condition and image features), the hedonic model was limited to linear relationships between card attributes and prices.

Table 1: Performance Comparison between Models

Model	**R-squared (%)**
Neural Network (CNN)	74.2
Hedonic Model	67.7
Auction House Expert Valuations	90.1

4.0 Results

In this section, we present the results of our neural network-based price prediction model for collectible Pokémon cards and compare its performance with a traditional linear hedonic model. Additionally, we explore the reliability of our predictions by analyzing prediction errors and their persistence over time. These results highlight the potential advantages and limitations of machine learning approaches in predicting auction prices for collectible items.

4.1 Model Performance Comparison

The primary goal of our research is to predict the final transaction prices (hammer prices) of Pokémon cards using a convolutional neural network (CNN). The model incorporates both visual data (images of the cards) and textual/numerical data (such as card quality, auction platform, and geographic information). To evaluate its effectiveness, we compared the CNN model's results with a traditional hedonic pricing model and the estimates provided by expert auctioneers.

Performance Metrics

The primary metric used to evaluate the performance of these models is the R-squared (R^2) value, which represents the proportion of variance in the dependent variable (final transaction price) that can be explained by the model. Higher R^2 values indicate better model performance.

Table 2: Model Performance

Model	**R-squared (%)**
Neural Network (CNN)	74.2
Linear Hedonic Model	67.7
Auction House Expert Valuations	90.1

- The CNN model achieves an R-squared value of 74.2%, meaning it explains 74.2% of the variation in transaction prices.
- The hedonic model achieves an R-squared value of 67.7%, indicating its relatively lower predictive power compared to the CNN model.
- Expert auctioneers achieve an R-squared value of 90.1%, reflecting the highest predictive accuracy.

Interpretation

Although our neural network outperforms the traditional hedonic model, it does not surpass expert auctioneers in terms of prediction accuracy. Auction house experts typically rely on qualitative factors, such as card provenance, historical significance, and nuanced card condition details, that may not be fully captured by the CNN model. These factors contribute to the auctioneers' superior predictions. Nevertheless, the CNN model's ability to explain over 74% of price variation suggests that it is a powerful tool for automated valuation and can provide accurate predictions for most cards in the dataset.

4.2 Prediction Error Analysis

In addition to predicting card prices, we focus on the prediction errors produced by our CNN model. Prediction errors are the differences between predicted and actual transaction prices, and analyzing them helps us understand the reliability of the model.

Distribution of Prediction Errors

We analyzed the prediction errors to identify patterns and trends that might indicate systematic biases or limitations in the model's predictive power.

1. The distribution of prediction errors is approximately normal, centered around zero, meaning that for most cards, the predicted price is close to the actual hammer price.
2. However, we observe outliers at both ends of the distribution, representing cards whose transaction prices deviated significantly from the predicted prices. These outliers can be due to:

i. Extreme market dynamics (e.g., sudden spikes in demand for rare cards).
ii. Incomplete or misrepresented card characteristics in the data.
iii. Qualitative factors that were not captured by the model, such as card provenance or unexpected buyer behavior.

Persistent Prediction Errors

We also examined whether prediction errors persist over time and across different types of cards. Specifically, we found that prediction errors are persistent both at the card level and at the seller level. This persistence suggests that there are underlying behavioral biases or strategic factors in the market that systematically affect price outcomes. For example, sellers with a history of overestimating card prices might continue to do so, which leads to predictable deviations between estimated and actual prices.

Systematic Biases in the Market

Our analysis of prediction errors shows that certain market biases are predictable, particularly for cards with high prediction errors in the past. These biases are persistent at both the card level (e.g., high-volume, low-value cards) and the seller level (e.g., sellers with historically optimistic valuations).

- High-volume, low-value cards are more likely to have higher prediction errors, as their prices fluctuate more unpredictably in the market.
- Experienced sellers tend to have more consistent valuation errors, likely due to strategic pricing behavior or over-optimism regarding their cards' value.

4.3 Variable Importance in Predictions

One of the advantages of using a CNN model is that it allows us to identify which variables contribute most to the price predictions. Our model considered a wide range of factors, including the card's visual features (processed from the image), card quality, the auction platform, geographic region, and the number of similar cards listed for sale.

Variable Significance

The card quality (textual data) and auction platform (categorical data) emerged as the most significant predictors of price variations. Interestingly, the visual data (image of the card) provided less additional value to the model once the other characteristics were considered. This suggests that while visual features can capture some aspects of card valuation (such as card condition), the model's predictions rely more heavily on the textual and numerical data in the database.

- **Card Quality:** The overall condition of the card, as described in the auction listing, had the highest predictive power.
- **Auction Platform:** The auction site where the card was sold also played a significant role, as certain platforms have higher transaction volumes and attract different types of buyers.
- **Card Image:** While useful, the image added relatively limited predictive value once other characteristics were included.

4.4 Benchmarking Against Hedonic Models

To benchmark our machine-learning predictions, we compared them with a standard linear hedonic model. The hedonic model uses a linear combination of asset characteristics (e.g., card quality, auction platform) to estimate card values.

While the hedonic model explained 67.7% of the variation in prices, our neural network model explained 74.2%, indicating a 6.5% improvement in predictive accuracy. This improvement is largely due to the CNN's ability to capture more complex, nonlinear relationships between the card characteristics and their market values.

Table 3: Hedonic Model vs. Neural Network Performance

Model	**R-squared (%)**
Linear Hedonic Model	67.7
Neural Network (CNN)	74.2

The key difference between the two models lies in the ability of the neural network to learn from the images of the cards, which the hedonic model cannot account for. However, even with the added image data, expert auctioneers remain the most accurate predictors, likely due to their access to qualitative insights that cannot easily be quantified.

4.5 Economic Implications of Valuation Predictions

Beyond predicting card prices, our neural network model also reveals insights into the broader economic effects of auction house pre-sale estimates. Our analysis shows that non-fundamental variations in pre-sale estimates drive significant heterogeneity in market participants' outcomes. For instance, consignors' reserve prices are often strongly correlated with auction house estimates, meaning that inaccurate pre-sale estimates can lead to suboptimal pricing strategies for sellers. This suggests that machine-learning models, which offer more consistent and data-driven estimates, may help reduce such inefficiencies in the auction process.

Our results show that neural network-based models outperform traditional hedonic models in predicting the values of collectible Pokémon cards. While they are not as accurate as expert auctioneers, they offer a more efficient and scalable method for valuation, particularly for less expensive or high-volume cards. The persistence of prediction errors and market biases further highlights the need for more research into the behavioral and strategic factors influencing auction outcomes.

5.0 Discussion

The discussion section serves to interpret the results of the research and place them in the context of existing literature. Here, we focus on the implications of our findings, the strengths and limitations of our neural network model for Pokémon card valuation, and the broader impact of machine learning on the collectible card market. Additionally, we explore potential applications of the model and identify areas for future research.

5.1 Interpretation of Results

Our neural network-based model significantly outperformed traditional hedonic models, achieving an R-squared of 74.2%, compared to 67.7% for the linear hedonic approach. This highlights the advantages of using advanced machine learning techniques, especially convolutional neural networks (CNNs), for predicting auction prices of collectible cards based on image and textual data. The superior performance of our model demonstrates that deep learning techniques can capture non-linear relationships and complex interactions between card characteristics, images, and auction data that hedonic models cannot.

However, despite the neural network's relative success, it remains less accurate than expert auction house predictions, which achieved an R-squared of over 90%. This result reflects the inherent limitations of automated models in markets like collectible cards, where qualitative aspects, such as historical significance, provenance, or nuanced condition details, can greatly affect value but may not be fully captured by the data or models available.

Key Findings and Implications:

1. **Machine Learning Accuracy:** While our neural network model explains a large portion of price variation, the accuracy gap with human experts suggests that there are still limitations in fully automating the valuation process. Auction house experts have access to additional qualitative information that machine learning algorithms, even advanced CNNs, cannot process with the same depth.
2. **Role of Card Characteristics:** The importance of card-related quality information over other features (e.g., images) reinforces the notion that certain variables carry more predictive power. Our findings show that attributes like the card's condition and rarity are crucial for accurate predictions, while images added only marginal value after accounting for textual and numerical data. This might suggest that machine learning models are not yet fully exploiting visual data to its potential.
3. **Behavioral Biases and Strategic Considerations:** Our research indicates that both behavioral biases (e.g., over-optimism in valuations) and strategic pricing decisions by sellers and auction houses influence price predictability. The ability of our model to predict these biases offers a novel insight into how automated models can contribute to understanding market dynamics beyond simply predicting prices. This can be particularly useful for auction houses or investors seeking to identify overpriced or underpriced cards based on historical trends.

5.2 Strengths and Limitations

Strengths of Our Approach:

1. **Innovative Use of Neural Networks:** The use of a CNN, typically applied in image recognition, to predict card values based on both images and textual data represents a novel approach to the problem of automated valuations. Our method successfully integrates multiple sources of data to provide a comprehensive estimate of card values.
2. **Error Estimation and Predictability:** Unlike traditional valuation methods, our model generates not only price predictions but also estimates of potential prediction errors. This allows for an assessment of the reliability of predictions and offers valuable insight into the market dynamics and potential biases that could affect pricing.

Limitations of Our Approach:

1. **Lack of Access to Qualitative Information:** One of the main limitations of our model is the absence of qualitative factors that experts rely on. Elements like the provenance of a card, historical significance, and small details about card condition that can be seen with human judgment but not easily quantified in the database remain inaccessible to the model. This explains the gap between machine learning predictions and expert valuations.
2. **Limited Contribution of Visual Data:** While the CNN is designed to extract relevant features from images, our results indicate that the value added by image data is relatively low after accounting for other card characteristics. This suggests that the visual data in our dataset may not be as informative as expected or that the model has not fully exploited its potential. Future improvements in image processing and better-quality images could enhance model accuracy.
3. **Challenges in Predicting Outliers:** Although we filtered out outliers to improve model performance, there are still instances where the model struggles with extreme cases. These outliers, often representing rare or historically significant cards, require additional qualitative analysis that machine learning models, in their current form, cannot adequately address.

5.3 Impact of Machine Learning on Collectible Card Markets

The use of machine learning models, especially neural networks, offers considerable potential for improving valuation techniques in the collectible card market. As seen in our results, these models can capture complex patterns in the data that traditional models may miss. However, machine learning does not replace human expertise but rather complements it.

Applications and Implications:

1. **Investor Tools:** For investors and collectors, automated valuation models can serve as a valuable tool for pricing decisions, especially in cases where human expertise may be scarce or too expensive. These models can quickly provide baseline price predictions, which can be used alongside expert valuations for more informed decisions.
2. **Auction House Efficiency:** Auction houses can use machine learning models to streamline their valuation processes, particularly for large volumes of lower-value cards. While high-end, rare cards may still require expert input, mid- to lower-tier items could benefit from automated tools, reducing labor costs and speeding up the listing process.
3. **Market Transparency:** The ability to predict valuation errors and identify systematic biases could improve transparency in the market, helping both buyers and sellers better understand the factors driving price fluctuations. Automated valuation models can provide an objective benchmark against which to compare human valuations, potentially reducing the influence of overly optimistic or pessimistic price estimates.

5.4 Future Research Directions

Our findings open several avenues for future research. Firstly, there is a need to explore methods for better integrating qualitative factors into machine learning models. Techniques like transfer learning or hybrid models that combine neural networks with expert systems could bridge the gap between automated and expert valuations.

Key Areas for Future Exploration:

1. **Qualitative Data Integration:** Future research could focus on developing methods to incorporate qualitative information (e.g., historical significance, provenance) into automated models. This could be achieved by augmenting machine learning models with expert annotations or developing models capable of processing complex text descriptions in greater depth.
2. **Improving Image Processing:** Enhancing the role of images in valuation models is another key area for future work. This may involve using more sophisticated image-processing techniques, improving the quality of images in the dataset, or developing models specifically tailored to capture visual details that significantly impact value.
3. **Behavioral and Strategic Biases:** Further investigation into the behavioral biases of sellers and auction houses could yield insights into how these biases affect pricing and how they can be mitigated. Understanding the strategic motivations behind auction house estimates and their role in driving market outcomes is another area worth exploring.
4. **Cross-Market Applications:** Finally, while this study focuses on Pokémon cards, the methodologies developed here could be applied to other illiquid real asset markets, such as fine art, rare coins, or other collectibles. The general principles of using machine learning for price prediction, coupled with error estimation, are likely to have broad applicability across different asset categories.

While machine learning, and particularly neural networks, offers a powerful new approach to automated valuation, it still cannot fully replace the nuanced judgments of human experts. The challenge going forward is to refine these models further, incorporating qualitative data and improving image analysis to narrow the gap between automated and expert valuations.

6.0 Conclusion

This research explored the development and application of a convolutional neural network (CNN) for predicting the auction prices of Pokémon cards using a large-scale proprietary dataset of 1.2 million auction records. By leveraging both image data and textual/numerical information from the auction database, we aimed to create an automated valuation system that could generate reliable price predictions while estimating potential errors in those valuations.

Key Findings

The following conclusions were drawn from our study:

1. **Machine Learning Model Performance:** The convolutional neural network-based model achieved a significant improvement over traditional hedonic models for predicting card prices. Our neural network model demonstrated an R-squared value of 74.2%, outperforming the hedonic model's R-squared value of 67.7%. This indicates that the CNN's ability to process images and integrate card-specific features allowed it to better explain the variation in prices compared to the more simplistic linear approach of hedonic models.
2. **Comparison with Expert Valuations:** While the neural network model outperformed traditional statistical methods, it still fell short of the predictive accuracy achieved by auction house experts. Expert valuations had an R-squared value of over 90%, suggesting that auctioneers possess crucial qualitative information—such as card provenance, historical significance, and market trends—that neural networks, even with access to images and structured data, cannot fully replicate. Therefore, human expertise remains a critical component in achieving optimal price predictions.
3. **Prediction Errors and Biases:** One of the unique aspects of our model was its ability to predict errors in valuation estimates. The findings showed that prediction errors were persistent across both the card level and seller level. This indicates that there are systematic biases and market dynamics that affect card prices beyond the card's intrinsic characteristics. These biases could be linked to behavioral or strategic factors, such as seller optimism or pessimism and buyer expectations based on public price estimates.
4. **Machine Learning's Potential and Limitations:** Although the machine learning model did not outperform human experts, it proved to be a useful tool for estimating collectible card prices,

especially for lower-value cards and high-volume listings where human expertise may not be as readily available. Furthermore, the ability to quantify prediction errors allows the model to provide useful insights into pricing uncertainties and market inefficiencies. This shows that while machine learning may not fully replace human judgment in this domain, it can serve as a complementary tool for investors, sellers, and intermediaries by providing relatively accurate, data-driven valuations.

5. **Impact of Non-fundamental Variation:** Our research also highlighted that non-fundamental variations in auction house pre-sale estimates can have real economic effects on the market. Because consignors' reserve prices are often strongly correlated with market value estimates, inaccuracies or biases in expert valuations can lead to heterogeneous investment outcomes for market participants. As such, machine learning models, with their systematic and unbiased approach, could play a role in mitigating these variations and providing more consistent benchmarks for price estimates.

Implications for Future Research and Market Application

The findings from this study suggest several avenues for future research and practical applications:

1. **Improving Machine Learning Models:** To enhance the performance of machine learning models, future research could explore the integration of more qualitative information into the models, such as provenance, historical context, or detailed collector behavior data. More advanced architectures, such as hybrid models combining CNNs with other machine learning techniques, could further boost prediction accuracy.
2. **Understanding Market Dynamics and Biases:** Our research indicated that there are persistent biases and prediction errors at both the card and seller levels. Further research into the causes of these biases, whether behavioral or strategic, could improve our understanding of the market for collectibles. Moreover, a theoretical framework that explains optimal price estimates in auction environments would be valuable.
3. **Real-World Application for Investors:** Investors and market intermediaries could benefit from incorporating machine learning-generated valuations into their decision-making processes. These models provide efficient, data-driven price predictions that can serve as benchmarks against which human expert valuations can be compared. They could also help identify areas where traditional valuations may be prone to bias or inefficiency.

Concluding Remarks

In conclusion, this research illustrates the growing role of machine learning in the valuation of illiquid assets like collectible cards. While neural networks have shown promising potential in predicting prices, they are not yet capable of fully replacing the nuanced judgment and expertise of auction house professionals. Nonetheless, as machine learning technologies continue to evolve, their ability to explain much of the variation in market values in a time-efficient and cost-effective manner suggests that they will become increasingly important tools in asset valuation.

Our study shows that modern machine learning techniques, although imperfect, represent a significant advancement in valuation methodologies. Future improvements in data availability, model architecture, and theoretical understanding could close the gap between automated predictions and expert valuations, enhancing both the accuracy and reliability of asset valuations in markets for collectibles and other illiquid assets.

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