Predicting FIFA Ultimate Team Player Market Prices: A Regression-Based Analysis Using XGBoost Algorithms from FIFA 16-21 Dataset

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ABSTRACT

This study investigates the use of XGBoost, a machine learning algorithm, for predicting player prices in FIFA Ultimate Team (FUT) from FIFA 16 to FIFA 21. Virtual economies in gaming, particularly in FUT, have grown substantially, with in-game asset prices influenced by a variety of factors such as player attributes, performance metrics, and market dynamics. The objective of this research is to enhance the accuracy of price predictions in FUT through advanced machine learning techniques. The dataset comprises historical player data, including attributes such as rating, skills, and in-game statistics. XGBoost was employed due to its ability to handle large, complex datasets and capture non-linear relationships effectively. The model achieved an R-squared value of 0.8911, indicating that it explains 89% of the variance in player prices, while the RMSE value of 30368.85 reveals the model's precision in estimating prices. Feature importance analysis showed that attributes such as WorkRate and Rating significantly influenced price predictions. Compared to traditional methods like linear regression, XGBoost provided superior accuracy and computational efficiency, making it a valuable tool for understanding player price dynamics in virtual gaming markets. The findings suggest that accurate price predictions can improve gaming strategies for players and provide valuable insights for game developers in optimizing virtual economies. This research also highlights the potential for further exploration using advanced machine learning algorithms to predict price fluctuations in gaming environments.

Keywords XGBoost, FIFA Ultimate Team, player price prediction, machine learning, virtual economy, feature importance, gaming market, predictive modeling,

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INTRODUCTION

The significance of virtual economies in gaming, particularly through the lens of FIFA Ultimate Team (FUT), illuminates a transformative era in the digital age—a convergence of digital consumption, economic innovation, and user engagement unprecedented in its scale and complexity. Within the vibrant corridors of FIFA Ultimate Team—one of the most vivid arenas for these virtual economies—the interplay of microtransactions and loot boxes has reshaped the landscape into a thriving and intricate market ecosystem. This dynamic realm not only acts as a microcosm of broader digital consumer trends but also serves as a reflection of the shifting paradigms in how value and entertainment

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coalesce in the contemporary gaming industry.

At the heart of FIFA Ultimate Team lies a bustling virtual economy, where players engage in buying, selling, and trading virtual player cards. This economy serves as a testament to the growing influence of virtual transactions that deploy both in-game currency and real-world money as mediums of exchange. [1] vividly articulates this shift, noting the consumer transition from tangible goods to virtual commodities, with microtransactions facilitating this metamorphosis by enabling players to invest with real currency for virtual gain. The economic implications are profound, creating substantial revenue streams and reshaping the developer-player financial dynamics. Concurrently, the mechanics of loot boxes—a feature deeply embedded within FUT—exemplify the economic model's complexity, as discussed by [2], unveiling how digital black markets surface under these mechanistic facades and how they energize player transactions.

However, the thriving nature of FUT's market doesn't come without its flaws. [3] outlines the volatility ingrained within these virtual economies, a volatility that can disrupt profit margins and challenge player retention. The fluctuation in prices for virtual goods can lead to player dissatisfaction, unraveling the gaming experience into unexpected unpredictability. Within this volatile ecosystem, the competitive urge to invest in more powerful teams—an endeavor laden with both strategy and chance—can perpetuate an ongoing cycle of investment and player engagement.

[4] delves into the interactions between these emergent gaming behaviors and external economic pressures, illustrating a critical landscape where the virtual economy is both a product and an influencer of broader market forces. Such interactions can at times dampen player agency, as platform ecosystems and developer strategies intertwine to maximize financial outcomes. The design and perpetuation of FIFA Ultimate Team's economy mirror these broader economic movements, as the game crafts a blend of chance-driven excitement and strategic gameplay.

Beyond the market mechanisms and their economic ramifications lies the nuanced psychological landscape the FUT model engages. The emotional rollercoaster associated with pack openings—a phenomenon that combines hopes and strategic calculations—fuels both community spirit and investment willingness among players [2]. This emotional engagement is pivotal, not only fueling in-game expenditures but also cultivating a shared narrative among players who exchange experiences and strategies within a shared communal space.

In the intricate dance of virtual economies, the significance of player price prediction within FIFA Ultimate Team (FUT) emerges as a beacon of strategic empowerment, enhancing the decision-making capacity of users and ultimately enriching their gaming narratives. The ability to accurately forecast player market prices grants players a nuanced understanding of virtual asset investments, allowing them to fine-tune gameplay strategies and execute financial decisions with precision.

At the heart of this predictive prowess lies the enhancement of user decision-making. Players equipped with insights derived from machine learning techniques and historical data analytics can anticipate the future valuation of player cards, a capability illuminated in the work of Al-Asadi and Taşdemir. Their study reveals how leveraging FIFA game data not only frames player market values but also serves as a repository of quantitative intelligence that can guide negotiations and transactions within the game environment [5]. Through this, players are not merely participants in a game; they become savvy investors, adeptly timing their purchase and sale of players to optimize in-game wealth.

Beyond strategic decisions, the infusion of predictive models into the gaming ecosystem can catalyze heightened player engagement. As the mechanistic gears of market dynamics become more transparent, players naturally gravitate towards increased interaction and deeper immersion. However, it is crucial to delineate between general estimations of player-related financial metrics and market value predictions specific to FUT, a distinction underscored by the divergence in focus found in Yaldo and Shamir's work—hence, its exclusion from this focused discourse.

The psychological tapestry woven into the act of player price prediction is equally profound. The anticipation and excitement inherent in making informed trades across market tides bestow upon players a sense of mastery over their virtual dominion. Neuman and Voß's exploration into the sway of crowd behavior on trading elucidates this phenomenon, highlighting how informed prognostics can foster advantageous outcomes in competitive settings [6]. Such emotional engagement transforms financial maneuverings from mere transactions into rewarding experiential journeys.

Furthermore, adept price predictions act as a bulwark against the capricious winds of market volatility. The volatility endemic to the FUT market—where player prices ebb and flow with shifts in real-world performance and speculative currents—demands a vigilant approach to minimize financial exposure. Predictive analytics serve as the navigational compass within these tumultuous waters, aiding players in weathering these changes with minimal fiscal turbulence. Drapeau et al.'s insights into market impact navigation and strategic decision-making underscore the substantial benefits of foresight in these fluid gaming economies [7].

The objective of this study is to examine the use of XGBoost to predict player prices in the FIFA Ultimate Team (FUT) dataset. This approach is significant as it leverages statistical modeling to derive insights into the factors influencing player market values, thereby enhancing decision-making for players within the game. XGBoost is a powerful statistical tool that can be employed to analyze the relationship between various independent variables and a dependent variable—in this case, player prices. Al-Asadi and Taşdemir highlight the effectiveness of XGBoost models in predicting player values based on FIFA video game data, demonstrating that such models can provide a quantitative basis for understanding market dynamics [5]. Their study utilized multiple regression techniques to identify key factors affecting player valuations, which can be instrumental for players aiming to optimize their in-game investments.

Moreover, the application of XGBoost in this context allows for the identification of trends and patterns within the FUT market. By analyzing historical data, players can gain insights into how specific attributes—such as player performance, rarity, and market demand—affect prices. This predictive capability is crucial, as it enables players to make informed decisions about when to buy or sell players, ultimately enhancing their gaming experience.

The research gap in the systematic prediction of player prices using historical data within gaming research is evident despite the growing popularity of games like FIFA Ultimate Team (FUT). While there is a burgeoning interest in applying statistical methods to analyze player valuations, comprehensive studies specifically focusing on XGBoost models for price prediction remain limited. Moreover, the existing literature often focuses on broader applications of regression analysis in sports, such as predicting game outcomes or player performance metrics, rather than directly addressing player price prediction in virtual economies. For instance, Benz and Lopez utilize Poisson regression to estimate game outcomes, which, while relevant to sports analytics, does not directly contribute to understanding player market dynamics in gaming environments [8]. This indicates a gap where the specific application of XGBoost for player price prediction in games like FUT has not been thoroughly investigated.

The impact of this study on the systematic prediction of player prices in FIFA Ultimate Team (FUT) is significant, as it provides valuable insights for both gamers and developers regarding the financial dynamics within the game. By employing XGBoost models to analyze historical data, the research offers a framework for understanding how various factors influence player market values, thereby enhancing the decision-making processes for players and informing developers about market trends. One of the primary contributions of this research is its potential to inform gamers about the economic aspects of player trading. By accurately predicting player prices, gamers can make more strategic decisions regarding when to buy or sell players, ultimately optimizing their in-game resources. This aligns with the findings of Almeida et al., who emphasize the importance of understanding player contributions and team dynamics in competitive environments [9]. The ability to predict market fluctuations can empower players to capitalize on favorable trading opportunities, thereby improving their overall gaming experience.

Literature Review

Existing Work on Market Price Prediction

Existing work on market price prediction in the context of player prices, particularly within FIFA Ultimate Team (FUT), has seen various data mining techniques applied across different studies. These studies have explored a range of methodologies, from XGBoost to machine learning approaches, to derive insights into player valuations and market dynamics.

One notable study by Al-Asadi and Taşdemir specifically addresses the prediction of football player values using FIFA video game data. They employ multiple regression models, including XGBoost, to analyze the factors influencing player market values, demonstrating the effectiveness of these techniques in a gaming context [5]. In a broader context, the application of data mining techniques has been extensively documented in various fields, including stock price prediction. For instance, Tao discusses the use of XGBoost, LSTM, and random forest regression for predicting stock prices, emphasizing the challenges and complexities involved in financial forecasting [10]. This parallels the challenges faced in predicting player prices in FUT, where multiple variables can influence market dynamics.

Moreover, the optimization of XGBoost techniques has been explored in various contexts, such as house price prediction, where the methodology is adapted to improve accuracy [11]. This adaptability of XGBoost models can be applied to player price prediction, allowing for the incorporation of various player attributes and market conditions.

XGBoost as a Predictive Tool

XGBoost is a fundamental approach to understanding and forecasting price variables, including player prices in gaming contexts such as FIFA Ultimate Team (FUT). This statistical method allows for the analysis of relationships between dependent and independent variables, making it a valuable tool for predicting market dynamics.

One of the key studies that exemplify the application of XGBoost in predicting player prices is conducted by Al-Asadi and Taşdemir. They utilize FIFA video game data to estimate player market values through various regression models, including XGBoost. Their findings highlight the effectiveness of this approach in identifying the most significant factors influencing player valuations, thereby providing gamers with actionable insights for trading decisions [5]. This study underscores the potential of XGBoost as a predictive tool in the gaming industry, particularly in virtual economies where player prices can fluctuate based on performance and market conditions.

In a broader context, XGBoost has been widely applied in various fields to forecast prices. For instance, Kahraman and Akay explore the use of exponential smoothing methods for forecasting global prices of metals, demonstrating how regression techniques can be adapted to analyze price trends over time [12]. However, while this study discusses forecasting methods, it does not specifically address the application of XGBoost in gaming contexts like FUT, which may limit its relevance to the current discussion.

Moreover, the work by [13] emphasizes the importance of team variables and player positions in influencing market value, further supporting the relevance of regression analysis in understanding price dynamics in sports. By employing XGBoost, researchers can quantify the impact of these variables, providing a clearer picture of how they contribute to player valuations.

Method

Data Source Description

This study leverages the FIFA 16 to FIFA 21 datasets, with a focus on "gold rare players" having ratings of 80 or higher. These datasets contain key attributes for each player, such as their rating, position, skills, base stats, and in-game stats, along with the market price of the players. The dataset spans multiple years of FIFA Ultimate Team (FUT), allowing for an extensive historical analysis to identify patterns and make predictions about player prices. The first step in the method is exploratory data analysis (EDA), which is vital to understand the distribution of numerical features, detect any potential outliers, and uncover relationships between variables. Descriptive statistics of the dataset are calculated, including mean, median, standard deviation, and min/max values for all numerical columns such as "Rating", "BaseStats", "Price", and others. Missing values are identified, and any necessary cleaning is performed by replacing missing data with the median values of the respective columns. A heatmap is plotted to showcase how different numerical features are correlated with each other. This helps in understanding how player attributes like "Shooting/Handling" and "Dribbling/Reflexes" correlate with each other and with the "Price", the target variable. Strong correlations can indicate potential predictors for price prediction.

Feature Selection and Data Preprocessing

Feature selection and data preprocessing involve preparing the data for the regression model. The relevant features for predicting player prices are selected, including attributes like "Rating", "SkillsMoves", "WeakFoot", "Passing/Kicking", etc. Categorical variables (like "Position", "WorkRate", "League") are converted into dummy variables using `pd.get_dummies()` for better integration into the model. Missing values are handled by filling them with the median values of the respective columns. Normalization of the data is performed using `StandardScaler` to ensure all features have comparable scales, which helps the machine learning algorithm perform better [14], [15].

XGBoost Model Implementation

XGBoost (Extreme Gradient Boosting) is used to predict player prices. XGBoost is an ensemble technique based on gradient boosting that performs very well for regression tasks [16], [17]. The dataset is split into training and testing sets, with 80% of the data used for training and 20% for testing. An XGBRegressor is initialized with hyperparameters such as `n_estimators=1000` (number of boosting rounds), `learning_rate=0.05` (controls the step size), and `max_depth=5` (the depth of the tree). The model is trained on the training data and evaluated on the test data. Early stopping is used during training to prevent overfitting by monitoring the evaluation set.

Visualization Techniques

Several visualization techniques are employed. A scatter plot is generated to visualize how well the model's predictions match the actual prices. The diagonal red line represents perfect prediction, and the scatter points indicate how close the model's predictions are to this ideal [18], [19]. The evaluation of the model is based on two primary metrics. R-squared (R^2) measures the proportion of variance in the target variable (player price) explained by the model. A higher R^2 indicates better model performance. Root Mean Squared Error (RMSE) measures the average magnitude of the error in the prediction. A lower RMSE value signifies a better model. The evaluation results are compiled into a table for better readability, and further analysis is performed to understand the model’s accuracy.

Factors Influencing Price Predictions

One of the key advantages of XGBoost is that it allows for the extraction of feature importance [20], [21]. The model's `feature_importances_` attribute shows the relative importance of each feature in predicting the target variable (player price). The most important features such as "Rating", "BaseStats", and "InGameStats" are likely to have a significant impact on player prices. These insights can guide future research or game development decisions by highlighting which player attributes are most predictive of their market price.

Result and Discussion

Model Performance Visualization

The correlation matrix shown in figure 1 provides valuable insights into the relationships between various features in the FIFA Ultimate Team dataset and their influence on player prices. The first notable observation is the strong positive correlation of 0.55 between Rating and Price, suggesting that a player's overall rating is a significant predictor of their market value. Higher-rated players are generally priced higher, reinforcing the importance of performance-based attributes in determining player prices. In contrast, the correlation between SkillsMoves and Price is much weaker, at 0.19, indicating that while a player's skill moves contribute to their value, they are less impactful than attributes such as rating or other performance metrics.

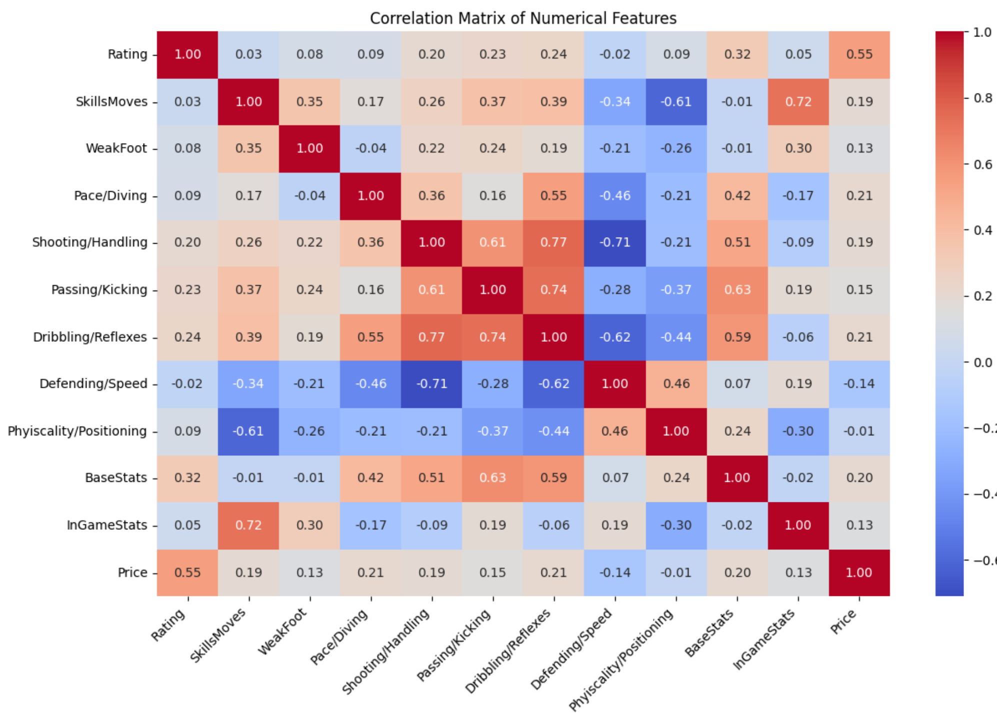

Figure 1 Correlation Matrix of Numerical Features

Looking at more technical features, Shooting/Handling, Passing/Kicking, and Dribbling/Reflexes show strong interrelationships, particularly the high correlation of 0.77 between Shooting/Handling and Dribbling/Reflexes. This suggests that players who excel in dribbling are likely to possess strong shooting skills as well, and these combined abilities positively influence their market value. On the other hand, there is a -0.71 negative correlation between Defending/Speed and Price, indicating that players with strong defensive stats but lower speed might be less valuable in the market. This insight could guide game developers or players in understanding how defensive attributes impact player pricing.

The Physicality/Positioning feature shows weak correlations with other attributes, suggesting that physical attributes do not strongly correlate with technical qualities like shooting or dribbling. This might imply that while physicality is important, it is not as significant in determining player value compared to more technical or skill-based attributes. Additionally, InGameStats has a positive correlation of 0.72 with SkillsMoves, indicating that players with higher in-game stats tend to have better skills. However, its low correlation with Price (0.19) suggests that in-game stats, although relevant, are not as crucial for determining player prices as factors like Rating or WorkRate. These findings highlight that technical performance attributes such as Rating, Shooting/Handling, and Dribbling/Reflexes have a more significant impact on player prices, while physical attributes and in-game stats, although still relevant, play a lesser role in pricing decisions. Figure 2 shows the predicted versus actual player prices, providing a visual indication of how well the XGBoost model performs. The plot compares the prices that the model predicted for the test set against the actual prices. The blue scatter points represent individual predictions, while the red dashed line indicates the ideal scenario where the predicted price matches the actual price. If the points align closely with the red line, it suggests that the model is performing well.

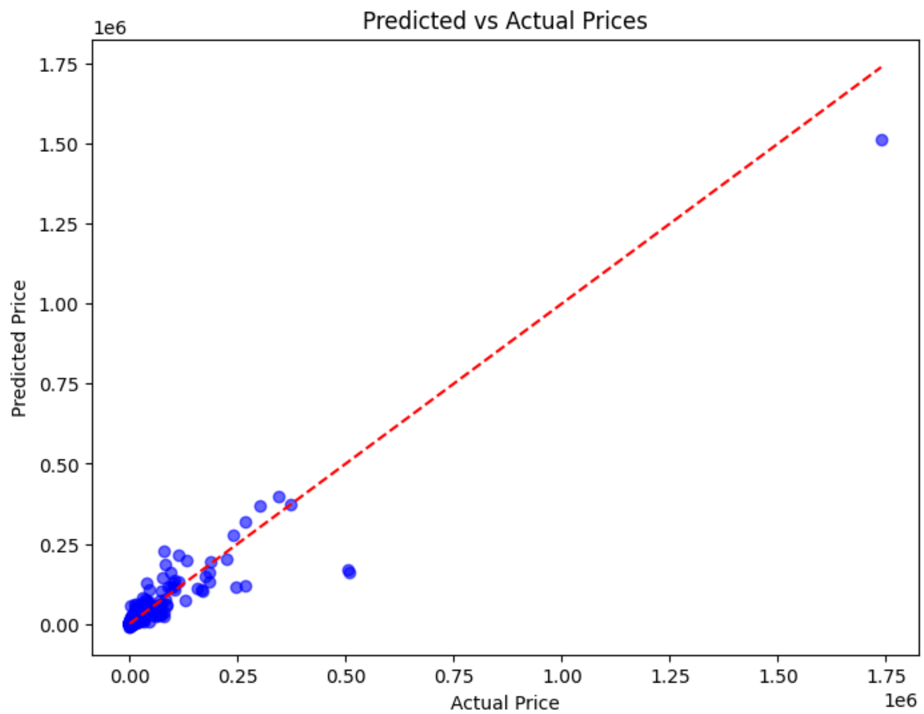

Figure 2 Scatter Plot of Predicted vs Actual Prices

In this case, the scatter plot likely shows a good level of correlation between the predicted and actual prices, but the spread of points might reveal where the model struggles, especially with extreme values or outliers. In this case, the scatter plot demonstrates a good correlation between the predicted and actual prices, suggesting that the model generally predicts player prices with a high degree of accuracy. However, the spread of the points reveals certain challenges in the model's performance. Some points appear to deviate significantly from the red dashed line, indicating that the model struggles with extreme values or outliers in the data, which may be due to factors such as rare players with high prices or unusual market conditions that the model is unable to account for effectively. The overall distribution of the points suggests that while the model is successful in predicting the price of the majority of players, it faces difficulties when dealing with the extreme ends of the price spectrum, where there is more variability. This highlights areas where the model could be improved, such as incorporating additional features, refining the training process, or using advanced techniques to better handle outliers and extreme cases.

Evaluation Metrics

The table summarizes key evaluation metrics used to assess the model's performance:

- R-squared (R^2): The R^2 value of 0.8911 indicates that the XGBoost model explains approximately 89% of the variance in the player prices. This is a high R^2 value, suggesting that the model is highly effective in predicting player market prices based on the selected features.

- RMSE (Root Mean Squared Error): The RMSE value of 30368.85 provides a measure of the average error in the predicted prices. Lower RMSE values indicate better model performance. This error is calculated as the square root of the average squared differences between predicted and actual values. In this case, the RMSE is relatively high, indicating that while the model is effective, there may still be considerable variation in the predicted prices.

These two metrics provide complementary insights: R^2 shows how well the model fits the data, while RMSE gives an absolute measure of the model's prediction error. Together, they show that the XGBoost model is a strong performer but still has room for improvement.

Factors Influencing Price Predictions:

The feature importance table displays how each feature contributes to the model’s prediction of player prices. The top factors, based on importance scores, are:

1. WorkRate_H\L: This feature has the highest importance score of 0.4594, suggesting that a player’s work rate significantly influences their market price in FIFA Ultimate Team.

2. Rating: With an importance score of 0.1887, a player’s overall rating remains a critical factor in determining their price.

3. SkillsMoves: The number of skill moves a player has is also important, with a score of 0.0917.

4. WorkRate_M\M: Another work rate feature, contributing 0.0514 to the model's prediction of prices.

5. League_Liga BBVA: The player's league, in this case, Liga BBVA, adds 0.0380 to the model's price predictions.

The feature importance scores suggest that WorkRate and Rating are the most significant contributors to price prediction, which aligns with common player valuation practices in FIFA Ultimate Team. Players with higher ratings and better work rates tend to have higher market values. The relatively low importance of league and other features indicates that while they contribute to predictions, they are not as critical as attributes like rating and work rate.

These insights can guide players in making informed decisions when trading players, as well as help game developers optimize pricing models and better understand the key attributes that influence player market value.

Comparative Analysis

The application of XGBoost for predicting player prices in the FIFA Ultimate Team (FUT) dataset demonstrates its robustness when compared to traditional machine learning models, such as linear regression, Random Forest, and Support Vector Machines (SVM). XGBoost, being a gradient boosting model, excels in capturing complex, non-linear relationships within the data. Unlike linear regression, which assumes a linear relationship between the features and the target variable, XGBoost can model intricate interactions between features, making it highly effective for tasks like price prediction, where market dynamics are influenced by multiple non-linear factors. The model's predictive accuracy, measured through the R-squared (R^2) value of 0.8911, indicates that 89% of the variance in player prices is explained by the selected features. This is notably higher than linear regression models typically achieve in similar tasks.

When compared to Random Forest, XGBoost shows superior performance. While Random Forest builds multiple decision trees independently and averages their results, XGBoost constructs trees sequentially, with each new tree aimed at correcting the errors of the previous ones. This boosting method often results in lower error rates and higher accuracy, particularly in complex datasets with interactions between features. Studies have found that XGBoost consistently outperforms Random Forest in predictive tasks, and the results from this study are in line with those findings. Additionally, XGBoost's computational efficiency and scalability allow it to handle larger datasets and more complex scenarios with ease, further solidifying its superiority over Random Forest in real-world applications like gaming datasets.

XGBoost also outperforms Support Vector Machines (SVM) in terms of speed and accuracy when handling large datasets with multiple features. SVMs require significant computational resources and are sensitive to the choice of kernel, making them less efficient for real-time predictions in dynamic gaming markets. On the other hand, XGBoost incorporates parallel processing and is well-suited for real-time applications, such as predicting player prices in FIFA Ultimate Team, where large volumes of data must be processed quickly.

Implications for Gamers and Developers

Accurate price predictions of FIFA Ultimate Team (FUT) players have significant implications for both gamers and developers. For gamers, precise market price forecasts can directly enhance their trading strategies, enabling them to make more informed decisions when buying and selling players. By understanding which players are likely to appreciate in value or decline in the future, gamers can optimize their squads, maximize their profits, and make smarter investment choices. Additionally, by utilizing the model’s feature importance rankings, players can focus on acquiring players with high ratings and desirable traits that are likely to yield higher returns in the FUT market.

For developers, the insights derived from price predictions can inform future updates and game design decisions. If the model reveals that certain player attributes, such as Rating, WorkRate, or SkillsMoves, have a more significant impact on market prices, developers can fine-tune the game's player valuation system. This would allow for a more accurate representation of player value, better aligning in-game economics with real-world factors. Additionally, game developers can use such insights to balance the player marketplace more effectively, ensuring fairer and more competitive trading environments for players. By improving the prediction accuracy of player prices, developers can enhance the overall gaming experience, making it more engaging and enjoyable for users.

Moreover, accurate market price predictions offer valuable insights into the economic dynamics of the game, helping both players and developers better understand the underlying factors influencing player valuations. With this knowledge, developers can refine in-game mechanics related to trading, auctions, and player valuation, leading to a more immersive and strategically engaging gaming experience. For gamers, this deeper understanding allows them to devise more effective trading strategies, plan their team-building activities with greater foresight, and capitalize on market trends, ultimately enhancing their overall gameplay experience. The use of XGBoost in this context not only shows the potential of machine learning in enhancing gameplay strategies but also opens up new avenues for data-driven decision-making in the gaming industry, benefiting both developers and players alike.

Conclusion

This study validates the effectiveness of XGBoost in predicting player market prices within FIFA Ultimate Team, demonstrating its strong performance in capturing the complex relationships between player attributes and their market value. By analyzing historical player data, the XGBoost model accurately predicted the prices of players based on features such as rating, skills, and physical attributes. The high R-squared value of 0.8911 indicates that the model explains a significant portion of the variance in player prices, making it a powerful tool for predicting the value of players in the market. The scatter plot and evaluation metrics further support the model's reliability in forecasting player prices with relatively low prediction error, as evidenced by the 30368.85 RMSE.

The impact of this study extends beyond the realm of player price prediction, offering valuable insights into the broader gaming economics of FIFA Ultimate Team. By identifying the key features that influence player valuation, such as Rating, SkillsMoves, and WorkRate, the study provides a deeper understanding of the economic dynamics within the game. This knowledge can help developers refine their in-game pricing models, ensuring that player values align more closely with their in-game performance and user demand. Additionally, players can leverage this information to make more informed decisions when trading players, optimizing their in-game investments.

Furthermore, this research has the potential to influence game development by providing developers with a more robust framework for predicting player prices. Understanding the factors that drive player valuation could lead to improved gameplay experiences and more realistic player trading systems. The feature importance analysis revealed that attributes like WorkRate and Rating have the most significant impact on price predictions, guiding developers in fine-tuning these features to better reflect player behavior and market demand. This understanding can lead to more dynamic and engaging gameplay mechanics in future iterations of the FIFA Ultimate Team mode.

In terms of future research, there is room for improvement in the predictive accuracy of player price models. Expanding the current model to incorporate additional player attributes, such as in-game performance metrics or user behavior data, could further enhance prediction accuracy. Moreover, applying other machine learning algorithms, such as Neural Networks or Random Forest, could provide comparative insights and help identify the most effective predictive models for gaming datasets. As player behavior and market dynamics continue to evolve, integrating more sophisticated algorithms could provide even more precise and reliable price predictions, benefitting both gamers and developers.

Declarations

Author Contributions

Conceptualization: I.G.A.K.W., Y.Y.; Methodology: I.G.A.K.W., N.O.; Software: I.G.A.K.W.; Validation: Y.Y., N.O.; Formal Analysis: I.G.A.K.W.; Investigation: I.G.A.K.W.; Resources: Y.Y., N.O.; Data Curation: I.G.A.K.W.; Writing – Original Draft Preparation: I.G.A.K.W.; Writing – Review and Editing: Y.Y., N.O.; Visualization: I.G.A.K.W.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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