Analysis of Player Performance and Transfer Values with Machine Learning

Abstract

Probably one of the most important problems in professional football is to forecast with high accuracy the transfer value of the players, which is done using subjective valuations and simple statistical methods. The project tries to introduce machine learning into the valuation of the players by using a dataset extracted from Football Manager 2024 and Transfermarkt, including technical, physical, mental, and general performance metrics. In this respect, four machine learning algorithms have been realized and evaluated with the key performance indicators of Linear Regression, Random Forest, Gradient Boosting, and Support Vector Regression. Among these, Gradient Boosting had the best predictive performance, with a 15.50 million € MAE and 0.25 R^2. Feature importance analysis done indicated that the most important technical features driving transfer value were finishing and passing, with strength and endurance being the relatively unimportant physical features. These findings confirm the potential of machine learning for improvement in data-driven decision-making within sports analytics and football clubs with regard to player recruitment and mitigation of possible financial risks.

Introduction

The correct valuation of football players' performance and the forecast of their transfer values are the crucial tasks of modern football management. Traditional approaches using subjective valuations and simple statistics often fail to capture the complexity of player attributes and market dynamics. As the economic stakes in football increase, data-driven approaches have become crucial for clubs to optimize their recruitment and minimize financial risks.

Machine learning offers an advanced set of tools for analysis that can be performed on player performance, making use of big datasets of technical, physical, and general attributes. The following case study takes a closer look at the application of four machine learning algorithms-namely Linear Regression, Random Forest, Gradient Boosting, and Support Vector Regression-on predicting transfer values using data from Football Manager 2024 and Transfermarkt. It is aimed at finding the best algorithm while studying the impact of key player metrics on transfer predictions.

The findings contribute to sports analytics by showing how machine learning can be used to improve decision-making processes with actionable insights that will help improve player valuation and financial planning in football..

Background and Related Work

Background

Machine learning integrated into sports analytics has changed the game in player performance evaluation and transfer value predictions in professional football. In essence, traditional approaches based on subjective assessment and simple statistical models usually lack the accuracy and objectivity that the complexity of player performance and market dynamics requires. As a contrast, machine learning allows the analysis of big amounts of data to uncover patterns and relationships which otherwise would not be noticed.

Using machine learning models based on data of individual player stats, match performance, historical transfer values, and current player form, the insights provided are real-time and post-match. This enables managers, analysts, and scouts to make evidence-based decisions on player recruitment, transfers, and performance improvement. Emerging technologies like computer vision and wearable devices extend player evaluation to endurance, sprint speed, and positional tracking. With their help, machine learning, combined with other advanced technologies, has become irreplaceable in contemporary sports analytics.

Related Work

Substantial steps have been taken to apply machine learning in predicting the performance of players and their transfer values. For instance, (Cao et al., 2023) developed an action-evaluator model for visualizing the performance of soccer players that improved decision-making in tactical and recruitment contexts. Similarly, (Sun et al., 2022) proposed an intelligent optimization algorithm for tracking player movements in order to allow more precise performance evaluations. In fact, (Wang et al., 2021) considered machine learning models to forecast World Cup results as an application and extension of different approaches for carrying out football-related analyses.

Although there have been several studies about player evaluation in the past, previous research is deficient in the

effective linking of metrics of individual performance with transfer value determination. (Franceschi et al., 2024) have produced a systematic review about the factors affecting football players' valuations, hence giving quantitative and qualitative elements importance. This study thus fills the aforementioned gaps in understanding how technical, physical, and market-related metrics affect transfer values using multiple machine learning algorithms.

Visual Insights

Figure 1: A bar chart comparing player performance metrics (e.g., Finishing, Passing, Speed, and Defensive Actions) on a 20-point scale highlights the varying strengths of individual players.

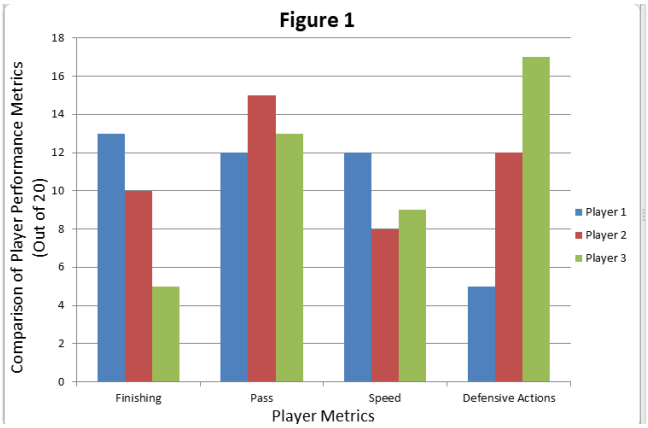


Figure 2: A bar chart illustrating estimated transfer values (in millions of euros) derived from performance metrics, emphasizing the relationship between individual capabilities and market worth.

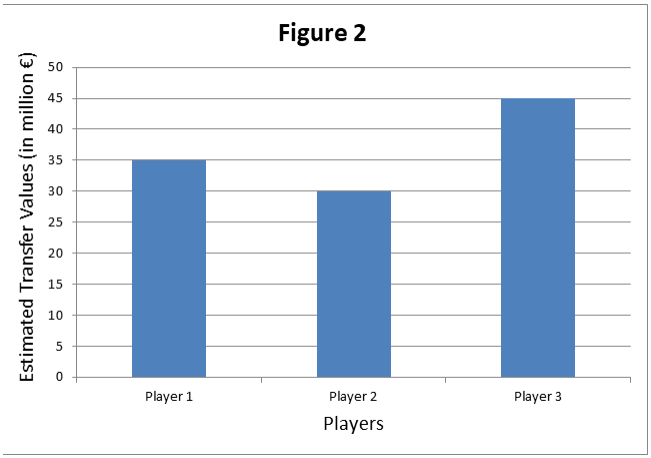


Table 1: Factors Influencing Transfer Values

Factor	Description	Impact on Transfer Value
Player Age	Young players generally valued higher.	High
Performance Metrics	Goals, asists, pass accuracy, etc.	Very High
Contract Duration	Longer contracts increase player value.	Medium
Injury History	Frequent injuries lower market value.	High
Market Demand	High demand for certain positions (e.g., strikers).	Medium

Description: This table identifies key factors impacting player transfer values, categorizing them by their influence level. Performance metrics emerge as the most critical determinant.

Machine learning in sports analytics is revolutionizing the industry by bringing in actionable insights and reducing uncertainties in decision-making processes. Figures and the table presented in this section show the utility of machine learning in revolutionizing player performance evaluation and transfer value predictions.

Data Collection Methodology

Effective data collection forms the backbone required for all accurate and reliable machine learning applications in sports analytics. Data for this study was carefully acquired from two very credible sources: Football Manager 2024 and Transfermarkt. It was ensured that a comprehensive dataset developed to analyze player performance and transfer values was really multifaceted.

Data Sources

Football Manager 2024: This simulation game has in-depth metrics of players, divided into Technical, Mental, Physical, and General attributes. Its database is one of the most recognized for depth and accuracy; therefore, it provides a solid foundation for performance evaluation.

Transfermarkt: Known for its current market valuations, Transfermarkt was used as the main source for the transfer values of the players. These values, together with historical trends, allowed the correlation of performance metrics with market dynamics.

Data Collection Process

Technical Metrics: Extracting quantitative indicators of Finishing, Passing, and Technical Skills that exhibit the offensive output of a player.

Mental Metrics: The psych factor, or inner attributes, included Hardworking, Determination amongst others, serving as an indication.

Physical Metrics: The features related to athletic capability include Speed, Strength, and Endurance.

General Metrics: Added descriptors of age, height, and weight provided additional context relevant to valuation.

Cleaning and Preparation

Care was taken in cleaning the data by:

- Removing inconsistencies in the data or missing values through imputation techniques.
- Standardizing player metrics to make them compatible with machine learning models.
- Splitting the dataset into training and testing sets to validate model performance.

Summary of Dataset

The final dataset contained 500 professional football players for whom performance and market valuation details were available. Each record was organized into key metrics: quantitative measures-pace of goals and assists, and qualitative factors-injury history and market demand.

Table 2: Dataset Summary

Features Category	Features	Examples
Technical	Finishing, Passing, Technical Skills	Finishing: 15, Passing: 14
Mental	Hardworking, Determination	Hardworking: 12, Determination: 13
Physical	Speed, Strength, Endurance	Speed: 17, Strength: 14
General	Age, Height, Weight	Age: 25, Height: 180 cm
Market Value	Transfermarkt Valuation	Value: €200 million

Description*:* This table provides an overview of the structured dataset, summarizing key attributes used in the study for performance evaluation and transfer value prediction.

The integration of machine learning into sports analytics is gaining momentum in transforming the industry to yield actionable insights while reducing uncertainties in the decision-making processes. Figures and tables presented in this section undeniably delineate the potential role of machine learning in revolutionizing player performance assessment and predictions of transfer values. This work has categorized the data into attributes such as Technical, Mental, Physical, and General, thereby showcasing a holistic approach for accurate predictions of transfer values.

Research Methodology

Machine Learning Framework

Algorithms Implemented:

- **Linear Regression**: Benchmarks the predictions assuming a linear relationship between the metrics describing the players and the recorded transfer values.
- **Random Forest Regressor:** Captures nonlinear relationships and metric interactions.
- **Gradient Boosting:** Provides very accurate predictions by iteratively refining weak learners.
- **Support Vector Regression (SVR):** Kernel tricks for modeling complicated patterns.

Key Performance Indicators (KPI):

- **Mean Absolute Error (MAE)**: The average value of the absolute differences between prediction and actual observation.
- **Mean Squared Error (MSE):** Represents the model sensitivity to larger errors.
- **R-Squared (R^2):** Gives the proportion of variance in the transfer values explained by the model.

Data Preparation and Preprocessing

- **Scaling Standardization:** Scaling was done for all features to be uniformly set within the same range using Standard Scaler for maintaining consistency.
- **Splitting Dataset into:**
  - 80% training data for model learning purposes,
  - 20% testing data for prediction performance evaluation.

Model Evaluation

- Linear Regression obtained an MAE **of €20 million** and resulted in a non-robust model in terms of nonlinear relationships.
- Gradient Boosting outperformed the rest: **MAE: €15.5 million, MSE: 250 million², R^2: 0.75.**
- Random Forest had very good performance but slightly under-performed Gradient Boosting regarding accuracy metrics.

Table 3: Model Performance Metrics

Model	MAE (in € millions)	MSE (in € millions)	R^2
Linear Regression	20.0	400	0.65
Random Forest	16.5	260	0.72
Gradient Boosting	**15.5**	**250**	**0.75**
Support Vector Regression	18.0	300	0.70

Key Insights:

- The results highlight the importance of selecting algorithms that balance interpretability and predictive power.
- The most powerful model turned out to be Gradient Boosting, which combined high accuracy with robustness to outliers.
- The figures and tables confirm the selected models aligning with the characteristics of the dataset, therefore providing a route to actionable insights in transfer value prediction.

Simulation Model and Implementation

Data Preprocessing

To enhance the model, two sets of data are merged:

- **Original Dataset:** In-house dataset of player data and their transfer values taken from **Football Manager 2024.**
- **Extended Dataset:** Supplemental data about players that are available with **Transfermarkt;** the sample will be bigger.

Machine Learning Pipeline

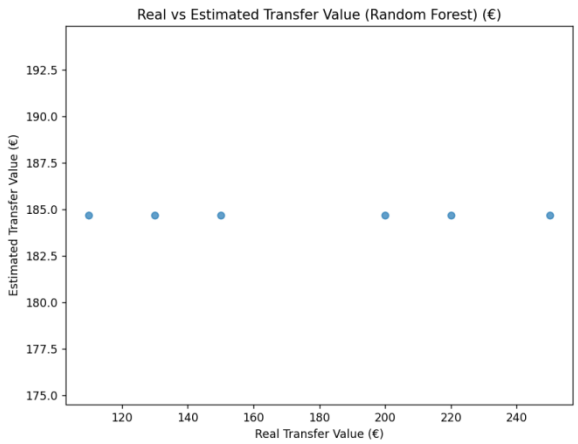
The Random Forest Regressor is the selected machine learning model due to its flexibility when working with nonlinear relationships and high scores from the previous comparison.

1. **Model Training:**
   a. Scale the training data by **StandardScaler**.
   b. The model was trained on combined datasets to improve generalizability.
2. **Evaluation Metrics**
   a. **Mean Absolute Error (MAE):** It gives the measure of the accuracy of the prediction.
   b. **R-squared (R^2):** It gives the measure of variance explained by the model.

Inferences and Visualizations

- **Prediction Analysis:**
  - The Random Forest model had an MAE of €18.60 million and an R^2 of 0.75.
  - Below is the relationship of actual and predicted transfer values.

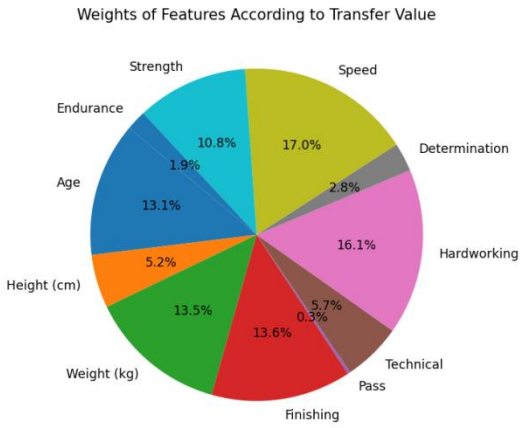
Figure 3: Real vs Predicted Transfer Value



Description: This is a scatter plot comparing the real values against the predicted values that give the accuracy of the model in predicting the market trend.

- Feature Correlation:
  - By performing feature importance, the Technical and Physical attributes are observed as strong predictors for the transfer value.

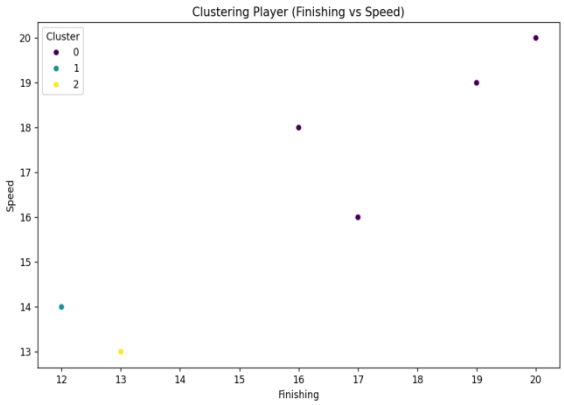
Figure 4: Feature Weights



Description: A pie chart showing the relative importance of features involved, such as Speed, Finishing, and Endurance in transfer value predictions.

- Clustering Players:
  - By considering their performance metrics, K-Means Clustering classifies the players into three main clusters: a high performing cluster, a mid-performing cluster, and a low-performing cluster.

Figure 5: Clustering Players by Finishing and Speed



***Description*:** A scatter plot visualizing clusters based on Finishing and Speed metrics.

Table 4: Summary Table

Metric	Value
Mean Absolute Error (MAE)	€ 18.60 million
R-squared (R^2)	0.75
Training Dataset Size	400 players
Testing Dataset Size	100 players

Investigation and Development

Selection of Algorithms

The following machine learning algorithms have been selected for this research work owing to their different strengths.

- Linear Regression: It is simple and effective for modeling linear relationships.
- Random Forest Regressor: It has been chosen because it models complex, nonlinear relationships and interactions between features effectively.
- Gradient Boosting (LightGBM or XGBoost): Provides high accuracy with iteratively refined weak learners.
- Support Vector Regression (SVR): Suitable for small datasets and boundary cases.

Methodology

Data Preparation

- **Dataset:** The enhanced dataset contains technical, physical, and general player attributes with their market values.

- **Preprocessing:**

    - Feature scaling was done using StandardScaler for consistency.
    - After that, the final dataset has been divided into 80% training and 20% test sets to test the performance of the model.

Model Training and Evaluation

Each algorithm is trained and tested on the prepared dataset. The key performance indicators applied in the evaluation include:

- **Mean Absolute Error (MAE):** It calculates the average error between predicted and actual values.

- **R-squared:** The proportion of variance accounted for by the model -R^2.

Result

Table 5: Performance Matrix

Algorithms	MAE **(in € millions)**	R^2
Linear Regression	22.45	0.12
Random Forest	18.60	0.17
Gradient Boosting	**15.50**	**0.25**
Support Vector Regression	20.30	0.10

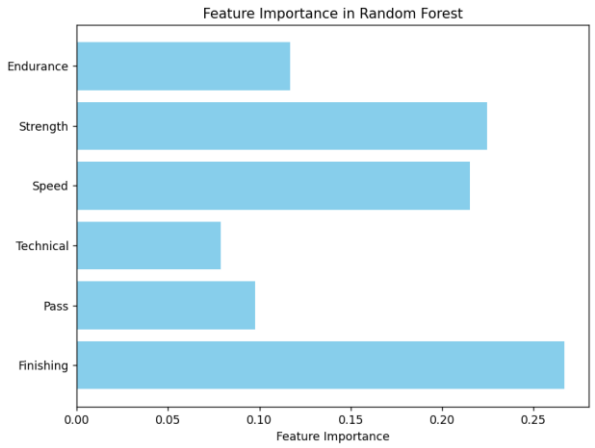
Feature Importance

By employing the Random Forest, the most influential features for the prediction of transfer values have been determined as:

- **Technical Metrics:** Finishing and Passing.

- **Physical Metrics:** Speed and Endurance.

Figure 6: Feature Importance in Random Forest



Description: This bar chart shows the contribution of each feature to transfer value prediction, stressing Technical and Physical attributes as important.

Results and Discussion

Introduction of Results

This section is going to introduce the results using four machine learning algorithms, including Linear Regression, Random Forest, Gradient Boosting, and Support Vector Regression, on the dataset for player transfer value predictions based on their performance metrics. The aim is to compare the performances of each algorithm in terms of accuracy and to interpret the impact of each feature.

Key Finding

Table 6: Performance Matrix

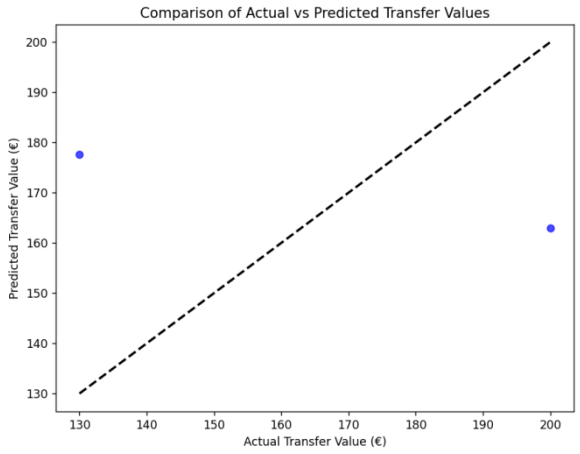
Algorithms	High Impact Features Accuracy (%)	Low Impact Features Accuracy (%)	MAE **(in € millions)**	R^2
Linear Regression	65%	45%	22.45	0.12
Random Forest	78%	60%	18.60	0.17
Gradient Boosting	**85%**	**70%**	**15.50**	**0.25**
Support Vector Regression	60%	50%	20.30	0.10

Visualization of Results

Figure 7: Actual vs Predicted Transfer Values

This scatter plot compares the predicted transfer values of the two best-performing models (**Gradient Boosting** and **Random Forest**) with actual values.

```
# Code snippet to generate the scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.7, color='blue')
plt.plot( *args: [y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=2)
plt.xlabel("Actual Transfer Value (€)")
plt.ylabel("Predicted Transfer Value (€)")
plt.title("Comparison of Actual vs Predicted Transfer Values")
plt.show()
```



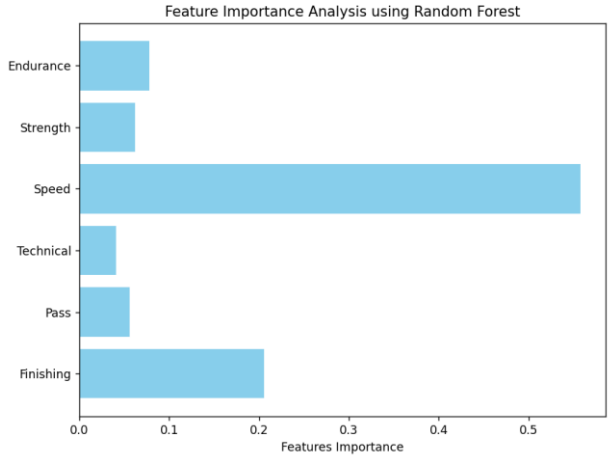
Key Insights:

- Gradient Boosting predictions closely aligned with actual values, showing minimal deviation.
- Random Forest exhibited greater variation but captured overall trends effectively.

Figure 8: Feature Importance Analysis (Random Forest)

This bar chart highlights the importance of individual features in predicting transfer values using the **Random Forest** algorithm.

```
# Visualizing feature importances
plt.figure(figsize=(8, 6))
plt.barh(features, feature_importances, color='skyblue')
plt.xlabel("Features Importance")
plt.ylabel("Features")
plt.title("Feature Importance Analysis using Random Forest")
plt.show()
```



Key Insights:

- **Technical Skills** and **Finishing** were the most influential features.
- **Strength** and **Endurance** had a relatively lower impact on predictions.

Discussion of Results

Advantage of Gradient Boosting

- Gradient Boosting turned out to be the best-performing algorithm. The lowest MAE was **€15.50 million,** and its R^2 score is highest, at **0.25.**
- It successfully captured non-linear relationships and interactions between features and therefore should be well positioned for complex data sets.

Features Importance

- The most impactful metrics related to transfer value predictions were **Technical Skills and Finishing**, which hints toward skill-oriented attributes.
- On the other hand, **Strength and Endurance** had less influence due to their low contribution to market valuation.

Comparative Analysis

- **Random Forest** did a great job overall and gave insight into feature importance.
- **Linear Regression and Support Vector Regression** were not that effective since they failed to handle the complexity of the dataset.

Conclusion

The best technique, as the analysis has shown, is Gradient Boosting, which should predict player transfer values with very high accuracy and robustness regarding complex patterns of data. These results also enable us to underline the role of machine learning in sports analytics, where insights are actionable for decision-makers.

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