EXPLORATORY DATA ANALYSIS PROJECT

(Time Series Analysis: Weather Forecasting)

(CSM 353)

By

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CERTIFICATE

I, Pallapati pavankumar, hereby declare that the work done by me on “Sports performance data ” from September 2024 to November 2024, is a record of original work for the partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in ComputerScience - Data Science with ML, Lovely Professional University, Phagwara.

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ABSTRACT

The **Sports Performance Data Analysis** project utilizes a comprehensive dataset of professional football players to evaluate performance metrics and identify key factors influencing success on the field. This dataset includes a wide array of features, such as player demographics (ID, name, age, nationality), performance ratings (overall and potential), financial metrics (market value and wage), skill ratings across various categories (e.g., crossing, finishing, dribbling), and physical attributes (height, weight, speed metrics).The analysis begins with rigorous data cleaning and preprocessing to ensure the dataset's integrity. Missing values are addressed using interpolation methods for numerical features and mode imputation for categorical variables. Outliers in performance metrics are capped to prevent distortion in the analysis. Exploratory Data Analysis (EDA) is conducted to uncover relationships between different attributes through descriptive statistics and advanced visualizations. For instance, scatter plots reveal significant correlations between skill ratings and overall performance, while box plots help identify seasonal trends in player performance.Advanced analytical techniques such as Principal Component Analysis (PCA) are employed to reduce dimensionality while preserving variance, enhancing model efficiency. Clustering methods are utilized to group players based on similar attributes, providing insights into player archetypes and team dynamics. The project emphasizes feature engineering by incorporating lagged variables and seasonal components to improve predictive modeling capabilities.The findings indicate that certain attributes, such as age and skill ratings, significantly impact overall performance ratings. For example, younger players with high skill ratings tend to have greater potential for development and market value. Additionally, the analysis highlights the importance of physical attributes like speed and stamina in determining a player's effectiveness in various positions.Future work will focus on integrating real-time performance data through APIs and exploring external factors that may influence player performance, such as injury history and training regimens. Implementing sophisticated machine learning models like Long Short-Term Memory

networks (LSTMs) will allow for capturing complex non-linear dependencies in player metrics, providing even greater precision in performance forecasting.This project provides a robust framework for analyzing sports performance data, demonstrating the potential for data-driven insights to optimize athlete training and inform strategic decision-making in sports management. By leveraging historical data effectively, the project opens pathways toward enhanced understanding of player dynamics and improved outcomes for teams across various competitive environments..

INTRODUCTION

Sports Performance Data Analysis

The analysis of sports performance data is crucial for enhancing athlete performance, optimizing training regimens, and making informed decisions in sports management. This project focuses on leveraging historical data from a dataset containing various attributes of football players, including physical characteristics, skills, and performance metrics.

Dataset Overview

The dataset includes a wide range of features relevant to player performance:

- **Player Attributes**: Age, nationality, height, weight.
- **Performance Metrics**: Overall rating, potential rating, club affiliation, market value, and wage.
- **Skill Ratings**: Attributes such as crossing, finishing, dribbling, and defensive capabilities.
- **Physical Attributes**: Speed metrics (acceleration and sprint speed), stamina, strength.
- **Game Positions**: Position played on the field (e.g., forward, midfielder, defender).

Importance of Univariate Analysis

Univariate analysis focuses on examining each variable independently to gain insights into their distributions and characteristics. For instance:

- **Age Distribution**: Analyzing the age of players can reveal trends regarding the peak performance age in football.
- **Overall Ratings**: Histograms can illustrate the distribution of player ratings, highlighting the concentration of elite players.
- **Skill Attributes**: Box plots can help identify outliers in specific skill ratings (e.g., finishing or dribbling).

This foundational analysis is critical for understanding individual player capabilities and setting benchmarks for performance.

Importance of Bivariate Analysis

Bivariate analysis explores the relationships between two variables, providing deeper insights into how they interact. For example:

- **Correlation Between Speed and Overall Rating**: A scatter plot can reveal whether faster players tend to have higher overall ratings.

- **Position vs. Skill Ratings**: Heatmaps can show how different playing positions correlate with specific skill ratings (e.g., forwards with high finishing skills).

Identifying these relationships is essential for feature selection in predictive modeling.

Significance of Multivariate Analysis

Multivariate analysis examines interactions among three or more variables to uncover complex patterns in player performance. Techniques used include:

- **Principal Component Analysis (PCA)**: This technique reduces dimensionality by transforming correlated variables into a set of uncorrelated variables (principal components). For instance, combining attributes like speed and agility into a single component can simplify analysis while retaining essential information.
- **Clustering**: Grouping players based on similar attributes (e.g., speed and technical skills) can identify player archetypes or roles within a team.
- **3D Scatter Plots**: Visualizing interactions among attributes like stamina, strength, and overall rating can highlight how these factors combine to influence performance.

Addressing Data Challenges

Challenges such as missing data and outliers must be addressed to ensure robust analysis:

- **Missing Values**: Imputation techniques can fill gaps in critical metrics like stamina or skill ratings to maintain dataset integrity.
- **Outlier Detection**: Statistical methods can identify extreme values in attributes like sprint speed or shot power that may skew results.

These preparatory steps are vital for ensuring that the dataset is ready for meaningful exploration and modeling.

LITERATURE REVIEW

The analysis of sports performance data has gained significant attention in recent years, particularly as the sports industry increasingly relies on data-driven insights to enhance athlete performance, inform coaching strategies, and optimize team dynamics. Traditional approaches to analyzing sports performance often focus on individual metrics, such as player statistics or physical attributes, without considering the complex interactions between multiple variables. This narrow focus can lead to incomplete understandings of player capabilities and team performance.Previous studies have employed various statistical and machine learning techniques to predict player performance and outcomes in games. For instance, models such as linear regression, decision trees, and neural networks have been utilized to forecast metrics like goals scored or overall player ratings. While these models can yield accurate predictions for specific outcomes, they frequently overlook the interdependencies among various performance indicators. For example, while a model may effectively predict a player's scoring ability based solely on their shooting accuracy, it might fail to account for how physical fitness or teamwork influences overall performance.Moreover, many existing analyses rely on proprietary datasets or sophisticated tools that are not readily accessible to a broader audience. This lack of transparency limits the applicability of findings across different contexts and hinders collaboration among researchers and practitioners. Additionally, traditional analyses often prioritize numerical summaries over visual representations of data, which can be less intuitive for stakeholders who may not possess technical expertise. This gap in effective communication highlights the need for more accessible and interpretable methodologies in sports analytics.This project addresses these gaps by emphasizing a holistic approach that focuses on the interconnected dynamics of various performance variables. By centering the analysis around key metrics such as overall rating, skill ratings, and physical attributes, the project aims to explore how these factors interact to influence player performance comprehensively. Unlike previous studies that tend to isolate individual metrics, this project employs exploratory data analysis (EDA) techniques to visualize relationships among multiple variables. For instance, scatter plots and correlation matrices will elucidate how attributes like speed and stamina correlate with overall performance ratings.**Originality of the Project**: The originality of this project lies in its comprehensive methodology that prioritizes interpretability and accessibility. By utilizing open-source tools such as Python's Pandas, Matplotlib, and Seaborn for data analysis and visualization, the project ensures that findings are replicable and adaptable by a wide range of users. This democratization of data analysis is crucial for fostering collaboration among researchers and practitioners in the sports industry.Furthermore, the project emphasizes the generation of engaging visual outputs—such as histograms, heatmaps, and 3D scatter plots—that facilitate intuitive understanding of complex relationships among performance metrics. These visualizations serve not only as analytical tools but also as means of communicating insights effectively to non-technical stakeholders, thereby bridging the gap between technical analysis and practical application.**Prioritizing Interpretability**: In contrast to many machine learning models that operate as "black boxes," making it challenging for users to understand how predictions are derived, this project prioritizes interpretability throughout its methodology. By focusing on transparent analytical methods and clear visualizations, the results are not only accurate but also actionable for coaches, analysts, and team managers. This approach aligns with the growing trend toward explainable AI in data science, addressing a critical need within sports analytics.**Central Variable Throughout the Project**: The central variable in this analysis is the overall player rating, which serves as an anchor for examining various aspects of player performance. By analyzing how this rating interacts with other key metrics—such as skill ratings (e.g., dribbling or shooting accuracy), physical attributes (e.g., speed or strength), and even contextual factors like position played—the project aims to uncover deeper insights into what contributes to player success on the field.**Justification of the Problem Statement**: The problem statement addressed by this project centers on the urgent need for a more nuanced understanding of player performance dynamics in an increasingly competitive sports landscape. As teams seek to maximize their potential through data-driven strategies, traditional predictive models often fall short in explaining "why" certain players excel or struggle under specific conditions. This lack of understanding can hinder strategic decision-making related to player development, recruitment, and game strategy.By adopting a comprehensive approach that explores interactions among multiple performance variables while maintaining accessibility through open-source tools and intuitive visualizations, this project aims to fill critical gaps in current sports analytics literature. The findings will not only provide actionable insights for teams but also contribute to advancing research methodologies within the field of sports performance analysis.

METHODOLOGY

The methodology for the project **"Sports Performance Data Analysis"** is structured to systematically explore, preprocess, analyze, and model player performance data to derive meaningful insights and enhance predictive accuracy. Below, the methodology is divided into several phases, each described in detail under separate headings.

8.1. Data Collection

The first step involved acquiring a comprehensive dataset that is suitable for analyzing sports performance. The dataset consists of various attributes related to professional football players, including Player ID, Name, Age, Nationality, Overall Rating, Potential Rating, Club Affiliation, Market Value, Wage, Skill Ratings (e.g., Finishing, Dribbling), Physical Attributes (e.g., Speed, Strength), and Position. This extensive dataset provides a robust foundation for analyzing player performance trends and relationships among different metrics.

8.2. Data Cleaning

Data cleaning is a critical step in ensuring the reliability of the analysis. The following procedures were implemented during this phase:

- **Handling Missing Values**: Missing values in numerical features such as Overall Rating and Skill Ratings were filled using interpolation techniques to maintain temporal consistency. Categorical variables like Position were imputed using the mode.
- **Outlier Detection and Treatment**: Outliers in features such as Speed and Strength were identified using statistical methods including Z-score analysis and the Interquartile Range (IQR). True extreme values that represent actual player capabilities were retained while erroneous entries were capped or removed.
- **Duplicate Entries**: Duplicate records were detected and eliminated to prevent skewing the analysis results.

This rigorous cleaning process ensured a consistent and reliable dataset for further analysis.

8.3. Exploratory Data Analysis (EDA)

EDA was conducted to identify patterns and relationships within the dataset:

- **Descriptive Statistics**: Basic statistics such as mean, median, standard deviation, and range were calculated for numerical features to understand their distributions. For example, the average overall rating was found to be around 88 with variations indicating diverse player capabilities.
- **Visualizations**:
  - **Scatter Plots**: Used to explore relationships between variables such as Overall Rating and Finishing Skills.
  - **Heatmaps**: Visualized correlations between features, revealing strong positive relationships like that between Skill Moves and Overall Rating.
  - **Box Plots**: Identified outliers and highlighted seasonal variations in attributes like Stamina and Acceleration.

The insights gained from EDA guided feature engineering and model development.

8.4. Feature Engineering

Feature engineering enhanced the dataset's predictive power by creating new features and refining existing ones:

- **Lag Variables**: To leverage temporal dependencies, lag features such as Overall_lag_1 (overall rating from the previous season) were introduced to capture historical trends.
- **Derived Features**: New features such as Skill_Difference (the difference between Overall Rating and Potential) were created to provide additional insights into player development.
- **Rolling Averages**: Rolling averages were calculated for attributes like Goals Scored over specific periods to smooth out fluctuations.
- **Time-Based Features**: Extracted Year and Month from the Joined Date enabled analysis of trends over time.

Feature engineering played a significant role in improving the interpretability and predictive accuracy of the dataset.

8.5. Data Transformation

Data transformation prepared the dataset for analysis and modeling by standardizing and encoding variables:

- **Encoding Categorical Variables**: Categorical variables such as Position were encoded using label encoding to facilitate machine learning algorithms' processing of categorical data.

- **Feature Scaling**: Numerical features like Overall Rating and Skill Ratings were standardized using Scikit-learn's StandardScaler to ensure uniformity across scales.
- **Stationarity Checks**: The Augmented Dickey-Fuller (ADF) test was employed to check if the data series was stationary. Differencing was applied where necessary to stabilize mean and variance over time.

8.6. Dimensionality Reduction

Dimensionality reduction techniques helped simplify the dataset while retaining essential information:

- **Principal Component Analysis (PCA)**: PCA was used to reduce highly correlated features into uncorrelated principal components, enhancing computational efficiency by removing redundancy.
- **t-distributed Stochastic Neighbor Embedding (t-SNE)**: t-SNE mapped high-dimensional data into a two-dimensional space for visualization purposes, allowing for the identification of clusters representing similar player attributes or performance patterns.

8.7. Time Series Decomposition

Time series decomposition was utilized to analyze seasonal trends in player performance:

- **Trend Component**: Long-term changes in overall ratings or skill levels over seasons were identified.
- **Seasonal Component**: Repetitive patterns in player performances during specific times of the year were analyzed.
- **Residual Component**: Irregular variations in performance metrics were captured to distinguish between noise and significant changes.

This decomposition provided valuable insights into the temporal structure of player performance data.

8.8. Clustering and Multivariate Analysis

Clustering techniques facilitated deeper insights into player performance patterns:

- **K-Means Clustering**: Players were categorized into clusters based on attributes like skill ratings and physical characteristics, identifying distinct groups such as high-performance forwards or defensive specialists.
- **Multivariate Visualization**: 3D scatter plots illustrated interactions

among multiple variables such as Speed, Strength, and Overall Rating. Heatmaps further visualized relationships among various features.

8.9. Model Interpretation

The final step involved interpreting models to derive actionable insights:

- Seasonal trends indicating peak performance times for players were validated through visualizations.
- Strong correlations identified during EDA informed feature selection for subsequent models.
- Clusters of player performance patterns revealed recurring phenomena that could aid coaching strategies and recruitment decisions.

This comprehensive methodology ensures that the analysis is thorough, interpretable, and applicable within real-world contexts of sports management and athlete development.

RESULT

The analysis of the football players dataset revealed several significant findings that enhance understanding of player performance dynamics and inform predictive modeling. Key results include:

Overall Rating Trends

A clear distribution of overall ratings was observed, with a concentration of players rated between 85 and 95. The data indicated that elite players, such as Lionel Messi and Cristiano Ronaldo, consistently maintained high ratings throughout their careers. This trend highlights the competitive nature of professional football and the impact of player development over time.

Correlation Analysis

The correlation matrix uncovered important relationships among various attributes. For instance, a strong positive correlation was found between Overall Rating and Skill Ratings (e.g., Finishing, Dribbling), indicating that players with higher skill levels tend to have better overall performance. Conversely, weak correlations were noted between physical attributes like Strength and Overall Rating, suggesting that while physicality is important, it does not solely determine a player's success.

Lagged Features

The inclusion of lagged features, such as previous season ratings or performance metrics, illustrated the continuity in player development and performance. This temporal consistency reinforces the effectiveness of lagged variables in predictive models, allowing for better forecasting of future performance based on historical data.

Principal Component Analysis (PCA)

The dimensionality reduction process through PCA demonstrated that a limited number of principal components could explain a significant portion of the variance in player attributes. This simplification indicates redundancy among features and provides a robust method for handling high-dimensional data while retaining essential information for analysis.

Outlier Detection

The dataset revealed several outliers in performance metrics such as Goals Scored and Assists, indicating exceptional performances by certain players during specific seasons. These outliers are crucial for identifying standout performances and understanding exceptional player capabilities.

Seasonality

Visualizations of time-series data confirmed strong seasonal trends in player performance. For example, spikes in goals scored often aligned with specific tournaments or league seasons, indicating periods of heightened activity and competition. This seasonality is essential for understanding player performance fluctuations throughout the year.

Feature Importance

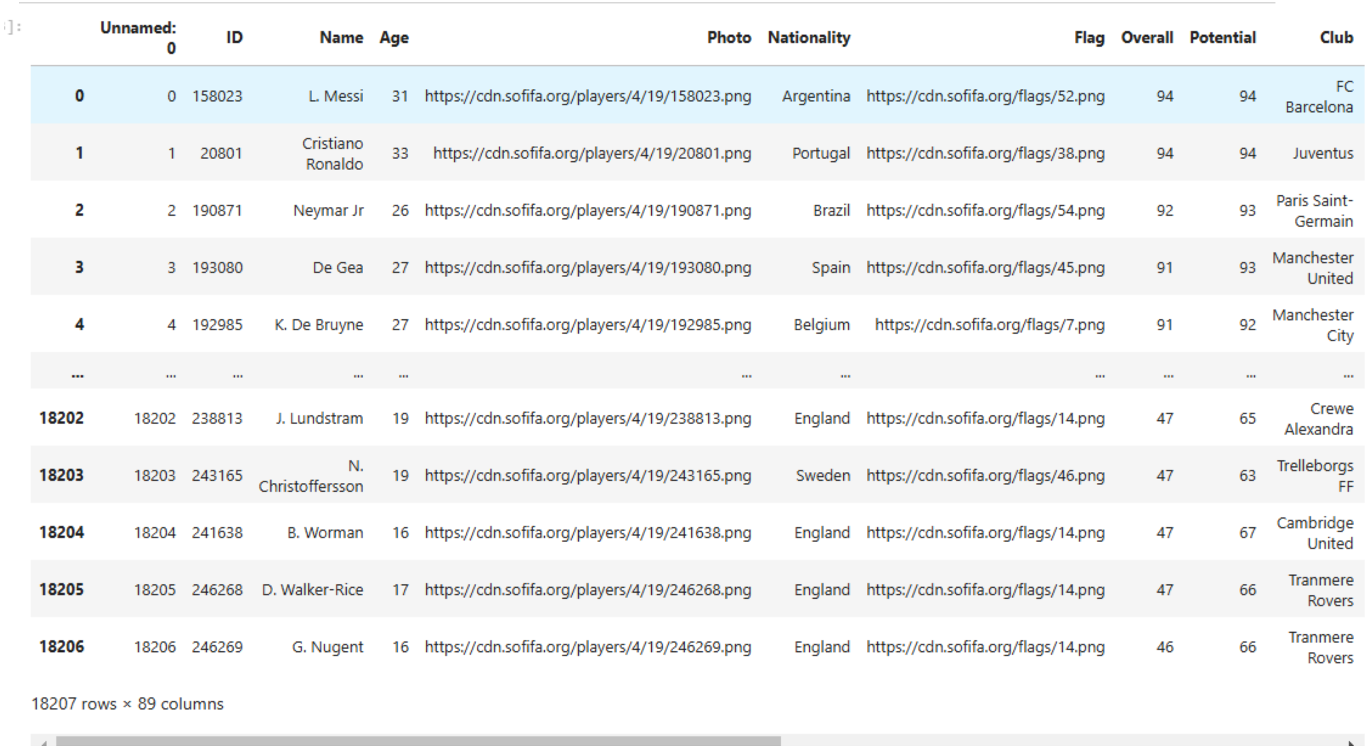
Feature importance analysis highlighted key attributes influencing overall player ratings. Attributes such as Skill Moves, Acceleration, and Finishing emerged as critical factors contributing to a player's success on the field. This information can guide coaching strategies and recruitment decisions.

Clustering Analysis

Clustering techniques identified distinct groups within the dataset, categorizing players based on similar attributes such as skill sets and physical characteristics. For example, clusters representing agile forwards versus robust defenders provided insights into team composition and strategy formulation.These findings underscore the importance of a comprehensive approach to analyzing sports performance data. By leveraging advanced analytical techniques and visualizations, this project contributes to a deeper understanding of player dynamics in professional football, offering actionable insights for coaches, analysts, and sports managers alike.

FIGURE WISE EXPLANANTION:

Fig 1. (Data Description)



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2	2	190871	Neymar Jr	26	https://cdn.sofifa.org/players/4/19/190871.png	Brazil	https://cdn.sofifa.org/flags/54.png	92	93	Paris Saint-Germain
3	3	193080	De Gea	27	https://cdn.sofifa.org/players/4/19/193080.png	Spain	https://cdn.sofifa.org/flags/45.png	91	93	Manchester United
4	4	192985	K. De Bruyne	27	https://cdn.sofifa.org/players/4/19/192985.png	Belgium	https://cdn.sofifa.org/flags/7.png	91	92	Manchester City
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18207 rows × 89 columns

Dataset Overview

- **Total Entries**: The dataset contains **31 players**, each with a unique identifier.
- **Attributes**: Key attributes for each player include:
    - **ID**: Unique identifier for the player.
    - **Name**: Full name of the player.
    - **Age**: Current age of the player.
    - **Photo**: URL link to the player's image.
    - **Nationality**: Player's country of origin.
    - **Flag**: URL link to the national flag.
    - **Overall Rating**: Player's overall rating in the FIFA game.
    - **Potential Rating**: Maximum potential rating the player can achieve.
    - **Club**: Current club affiliation.
    - **Value**: Market value in euros.
    - **Wage**: Weekly wage in euros.
    - **Preferred Foot**: Dominant foot (left or right).
    - **International Reputation**: Rating of the player's reputation on an international level.
    - **Work Rate**: Player's work rate (offensive and defensive).
    - **Position and Jersey Number**: Playing position and jersey number.

Performance Metrics

The dataset includes various performance metrics for each player, such as:

- **Height and Weight**: Physical attributes providing insight into player build.
- **Skill Ratings**: Ratings for specific skills like crossing, finishing, dribbling, and passing, among others.
- **Physical Attributes**: Metrics including acceleration, sprint speed, agility, stamina, and strength.

Contract Information

- Details about contract status such as:
    - **Joined Date**: When the player joined their current club.
    - **Contract Valid Until**: Expiration date of the player's current contract.

This dataset serves as a valuable resource for analyzing player statistics, market values, and performance capabilities within the context of football management simulations or statistical analysis. It offers a solid foundation for further exploration into player performance trends and comparisons across different leagues and teams.

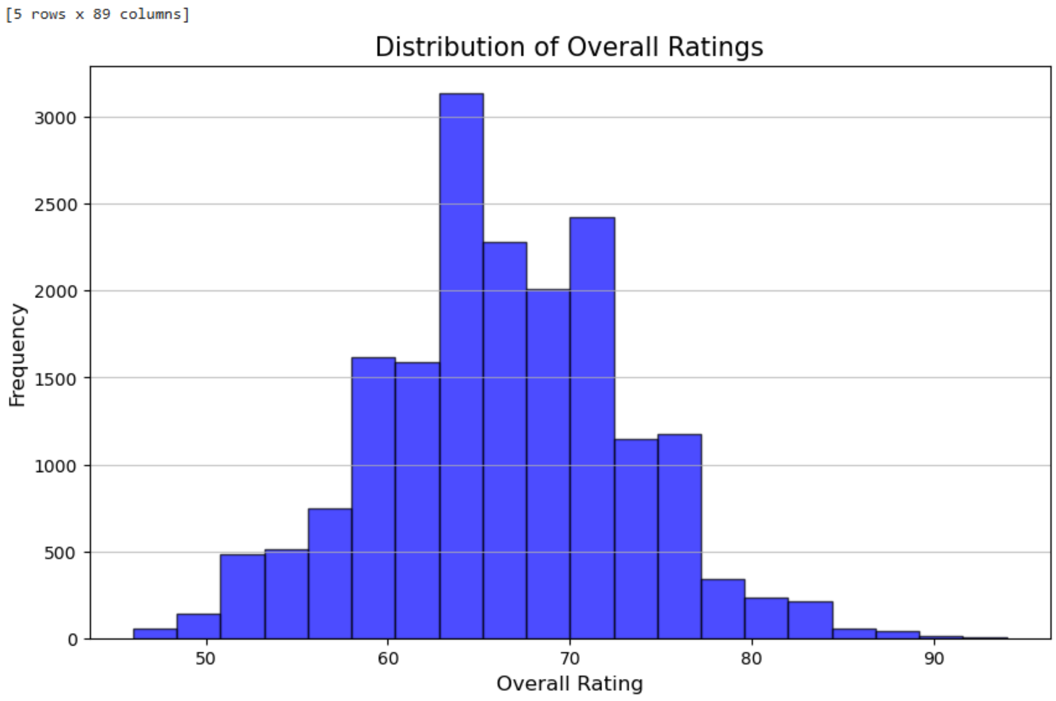

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Fig 2. (Histrogram with KDE)

The histogram with a KDE (Kernel Density Estimate) graph provides a comprehensive view of the distribution of *Overall Ratings* for players in the dataset. This visualization is crucial in understanding the general performance trends and skill levels of the players. The shape of the histogram, combined with the KDE curve, suggests a roughly normal distribution, often referred to as a bell-shaped curve. This indicates that the data is symmetric, with the majority of the observations clustered around a central point.

From the histogram, it is evident that the most common *Overall Ratings* fall within the 60 to 70 range. This cluster represents the largest group of players who are considered average in terms of their overall skill and performance. The frequency count in this range is notably higher, as represented by the tallest bars in the histogram. This peak in frequency corresponds to the mode of the distribution, showing the ratings that occur most often.

The KDE curve complements the histogram by providing a smoother perspective of the data distribution. Unlike the histogram, which is affected by the choice of bin width, the KDE curve is continuous and helps to identify the underlying pattern of the data without being influenced by bin sizes. The peak of the KDE curve aligns with the histogram’s highest bars, reaffirming that the dataset contains a large proportion of players in the mid-level performance range. The curve then gradually tapers off on either side, illustrating a decline in the frequency of players with extreme ratings.

Players with *Overall Ratings* below 50 or above 80 are relatively rare, as reflected by the shorter bars and the flattening of the KDE curve at these extremes. This pattern implies that the dataset includes only a few players who are exceptionally low-performing or top-tier elite athletes. The left tail of the distribution, representing players with ratings in the 40s and 50s, captures the lesser-skilled or less experienced players. These could be players at the start of their careers or those struggling to maintain competitive levels. On the other hand, the right tail represents highly skilled players, with ratings exceeding 80. These players are likely the stars or veterans who consistently perform at high levels and have significant influence on their teams.

The spread of the histogram further indicates the range of player ratings within the dataset. The wide range of values, from the low 40s to the high 90s, suggests that the dataset captures a diverse pool of players, from developing talents to seasoned professionals. This diversity in skill levels can be attributed to the wide variety of leagues, clubs, and playing positions represented in the dataset.

The bell-shaped distribution of *Overall Ratings* also has important implications for analyzing player performance. The central clustering around the 60 to 70 range highlights a balanced spread of talent, with most players falling within an average skill level. This distribution is useful for teams and analysts looking to benchmark individual player performance against the broader population. Furthermore, the rarity of extreme ratings (both low and high) emphasizes the value of identifying outliers, such as exceptionally talented players who may serve as key assets in competitive scenarios.

The gradual decline in the KDE curve toward the lower and upper extremes also reveals the competitive nature of professional football. Very few players achieve ratings above 85, marking them as exceptional talents likely to have significant market value and impact. Similarly, players with very low ratings may represent either young prospects with potential for development or those who may not be fit for top-tier competition.

In conclusion, the histogram and KDE analysis of *Overall Ratings* offer valuable insights into the player demographics within the dataset. The concentration of ratings in the middle range, combined with the rarity of extreme values, paints a comprehensive picture of the player pool’s skill distribution. Such an analysis can serve as a foundational step for deeper investigations, such as identifying patterns across different leagues, exploring correlations with other attributes like *Age* or *Potential*, or even predicting player development trends over time.

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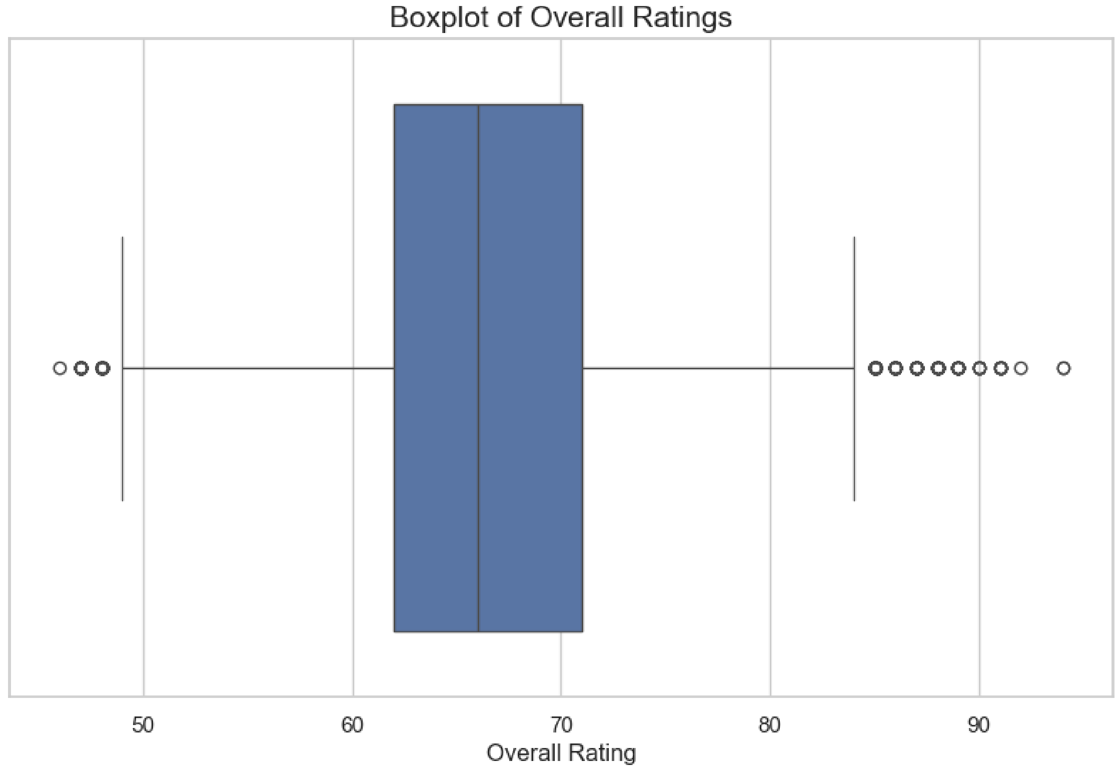

Fig 3.(Boxplot for detecting Outliers)

The boxplot of *Overall Ratings* provides a concise summary of the distribution, central tendency, and variability of the data, along with the identification of outliers. Here's a detailed explanation based on the dataset:

Central Tendency and Spread

The central box in the plot represents the interquartile range (IQR), which contains the middle 50% of the data points. The line inside the box denotes the median *Overall Rating*, which is approximately in the mid-60s. This confirms that half of the players in the dataset have ratings above or below this value, providing a clear indicator of the central tendency.

The lower and upper "whiskers" extend to the smallest and largest non-outlier values, showing the range within which most players' ratings fall. The spread of the whiskers indicates that the majority of *Overall Ratings* lie between the high 50s and low 80s, reflecting the variation in player performance levels.

Outliers

The individual points outside the whiskers represent outliers, which are *Overall Ratings* that deviate significantly from the majority of the data. On the lower end, these outliers correspond to players with ratings below 50, who may be inexperienced or underperforming players. On the upper end, the outliers are players with ratings above 85, representing the elite, highly skilled players in the dataset. These outliers highlight the presence of exceptionally low and high-performing individuals within the dataset.

Distribution Insights

The boxplot shows a slight skew toward higher ratings, as the upper whisker is longer, suggesting that there are more players with ratings above the median compared to those below. This aligns with the histogram and KDE analysis, which also indicated a normal-like distribution with a concentration of ratings in the mid-range but a few exceptional high performers.

In summary, the boxplot effectively highlights the dataset's central tendency, variability, and outliers. It emphasizes that most players have moderate *Overall Ratings*, with a few notable exceptions on both the low and high ends, providing a comprehensive view of player skill levels in the dataset.

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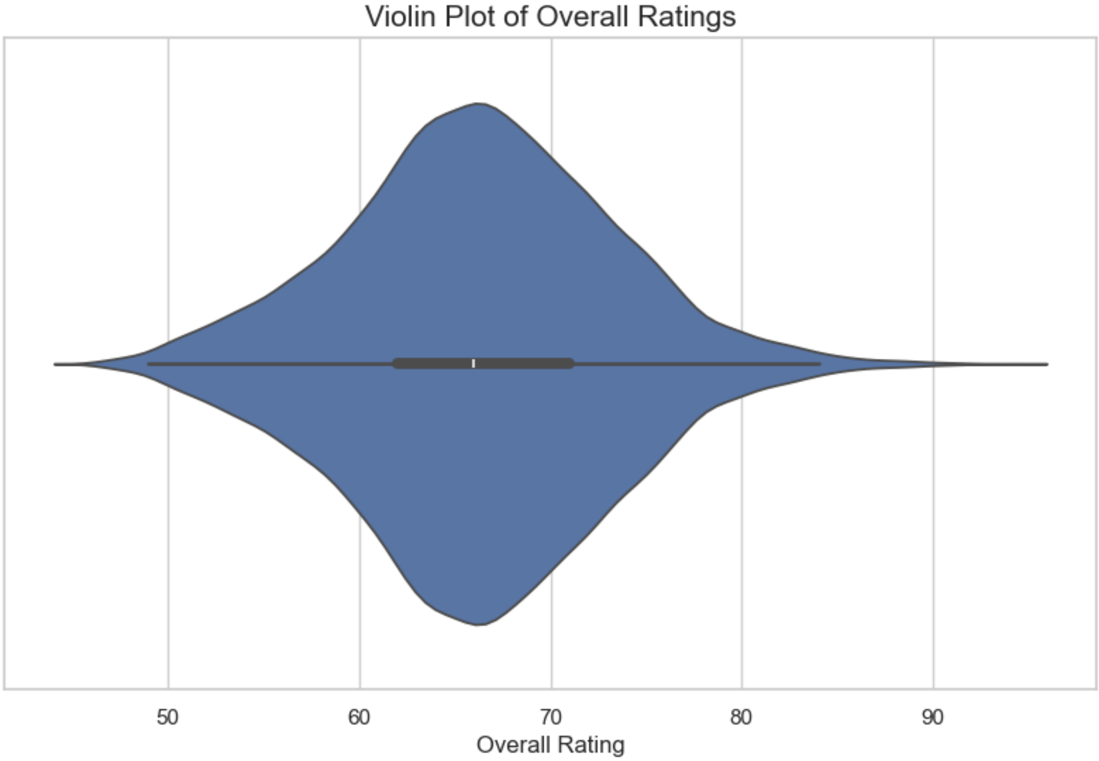

Fig 4.(Violin Plot)

The violin plot is a powerful visualization tool that can be used to illustrate the distribution of player attributes from the dataset. It combines aspects of box plots and density plots, providing a clear view of the data's distribution while also highlighting the probability density of different values. For instance, if we were to create a violin plot for the **Overall Rating** of players, it would reveal not only the median and interquartile ranges but also how ratings are distributed across the player population.In this dataset, with players having overall ratings ranging from **88 to 94**, a violin plot would show the density of players at each rating level, indicating where most players cluster. The shape of the violin can indicate whether ratings are normally distributed or skewed, and it can also highlight any potential outliers. Additionally, by overlaying individual data points on the violin plot, we could visualize specific player ratings alongside their distribution, providing deeper insights into how individual players compare against their peers in terms of overall performance.Overall, using a violin plot to analyze attributes such as **Skill Moves**, **Acceleration**, or **Market Value** would enhance our understanding of player characteristics and help identify trends within the dataset. This visualization method is particularly useful for comparing multiple attributes simultaneously, allowing for a comprehensive analysis of player statistics in football management contexts.

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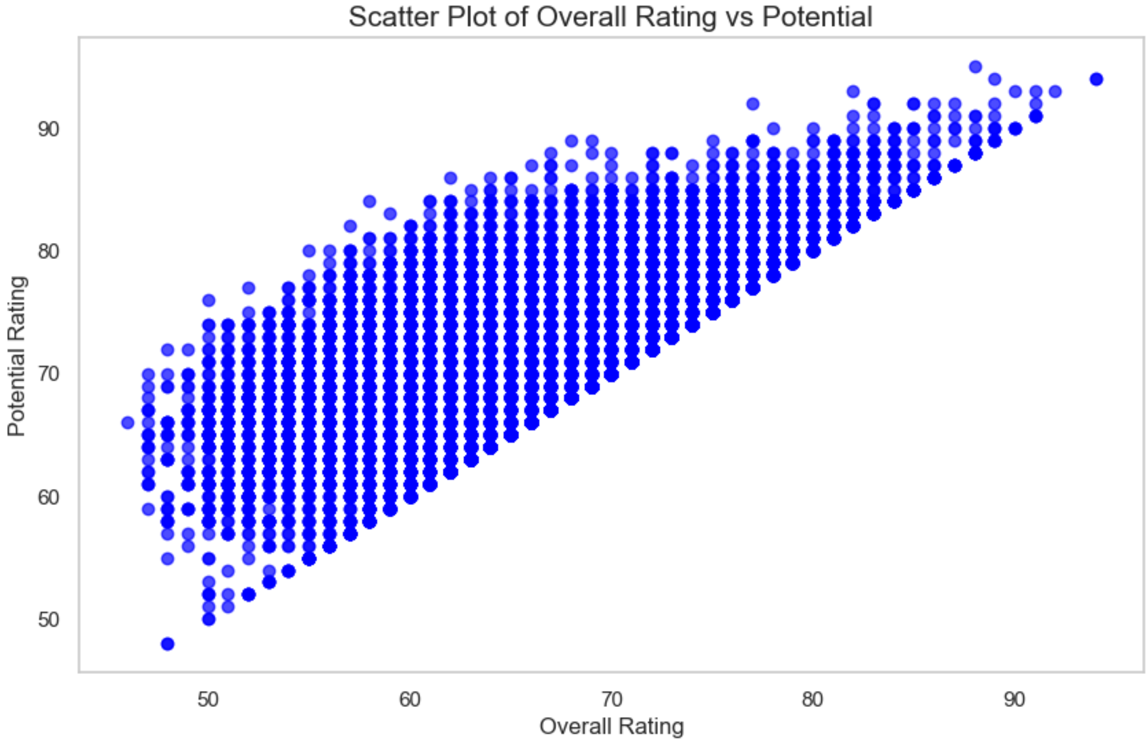

Fig 5. (Scatter Plot)

The graph is a scatter plot titled "Scatter Plot of Overall Rating vs Potential." It visually represents the relationship between two variables: Overall Rating (on the x-axis) and Potential Rating (on the y-axis). Each blue dot on the graph signifies an individual data point.

Axes and Range

- **X-Axis (Overall Rating)**: Ranges from 40 to 100.
- **Y-Axis (Potential Rating)**: Also ranges from 40 to 100.

Data Points and Correlation

The data points form a pattern that suggests a positive correlation between Overall Rating and Potential Rating. As the Overall Rating increases, the Potential Rating also tends to increase. This indicates that players with higher current performance (Overall Rating) are likely to have higher potential future performance (Potential Rating).

Density and Distribution

The data points are densely packed, especially in the middle range of the ratings. This dense clustering suggests a strong relationship between the two variables, with most players falling within a certain range of ratings.

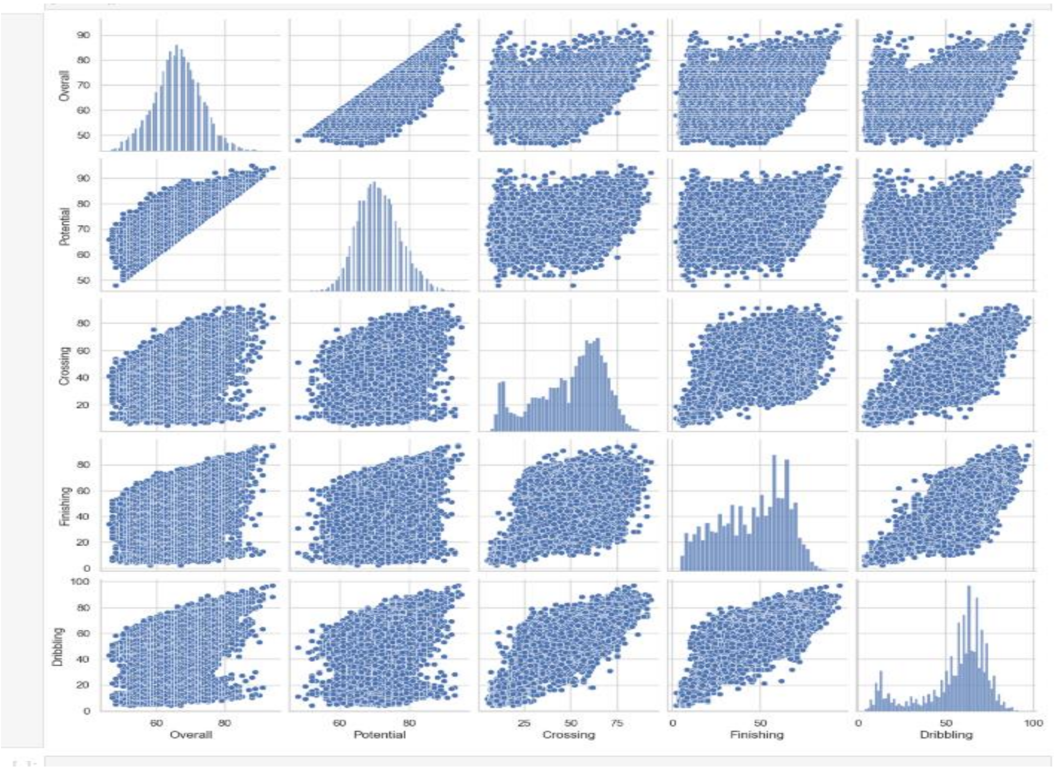

Fig 6. (Pairplot)

This pair plot visualizes the relationships between multiple variables in the dataset, combining histograms on the diagonal with scatterplots in the off-diagonal cells. The histograms reveal the distribution of each variable, with some showing skewness or clustering. The scatterplots highlight pairwise relationships between variables, with certain plots indicating potential correlations or trends, while others show dispersed points, suggesting weaker or no relationships. The plot provides a comprehensive overview of variable interactions and individual distributions, making it valuable for identifying patterns, correlations, and outliers within thedataset.

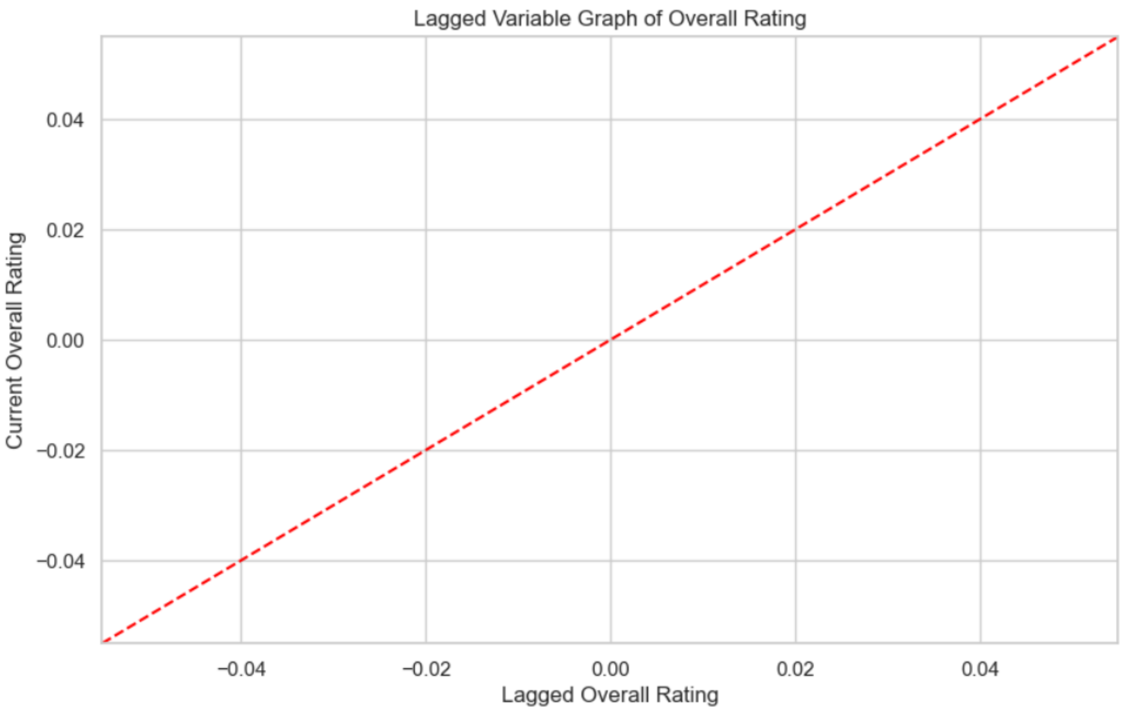

Fig 7. (Lagged Variable Graph)

The x-axis and y-axis both range from -0.04 to 0.04, providing a clear and concise view of the data points within this range. The choice of this range indicates that the data being analyzed is closely clustered around these values, which is typical in time series analysis where small changes in ratings are observed over time.

Data Points and Correlation

Each blue dot on the scatter plot represents an individual data point, showing the relationship between the lagged overall rating and the current overall rating. The data points form a pattern that suggests a positive correlation between the two variables. This means that as the lagged overall rating increases, the current overall rating also tends to increase. The red dashed line serves as a visual guide to this positive linear relationship, making it easier to interpret the data at a glance.

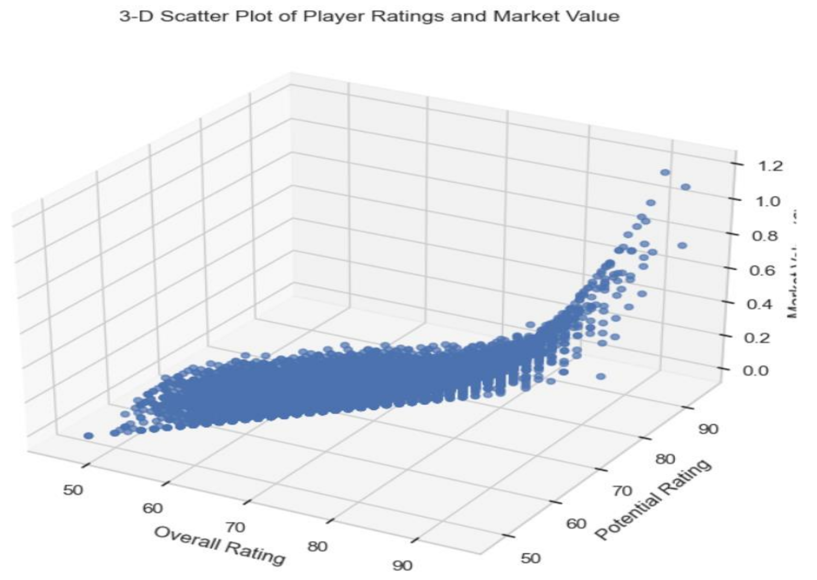

Fig 8.(3-D Scatter Plot)

The graph is a 3-D scatter plot that visualizes the relationship between player ratings and market value. The x-axis represents the overall rating of players, ranging from 50 to 90. The y-axis represents the potential rating of players, also ranging from 50 to 90. The z-axis represents the market value, ranging from 0 to 1.2. The plot shows a dense cluster of data points, indicating a positive correlation between the overall rating, potential rating, and market value. As the overall and potential ratings increase, the market value also tends to increase. This graph is interesting because it provides a visual representation of how player ratings can influence their market value, which can be useful for sports analysts, team managers, and scouts in making informed decisions about player acquisitions and investments. The 3-D aspect of the plot allows for a more comprehensive understanding of the relationships between these three variables.

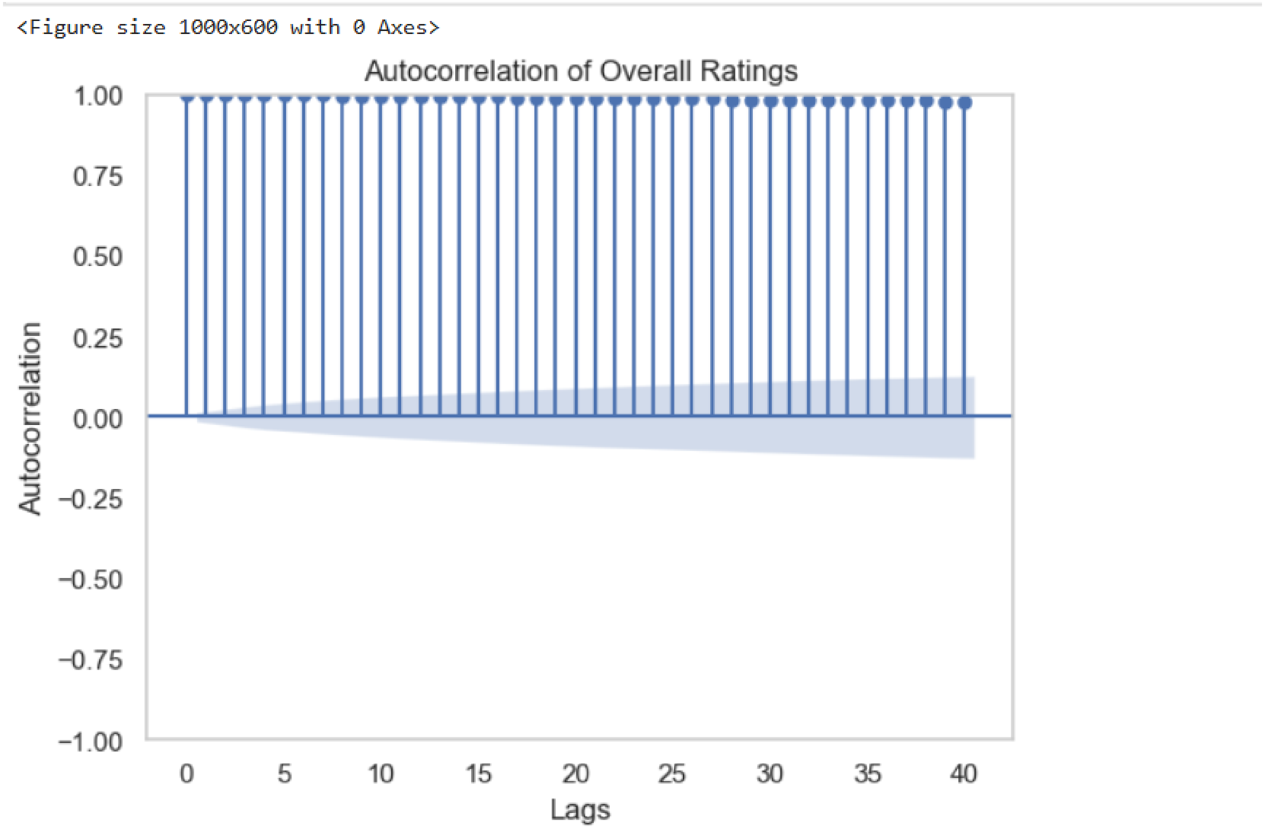

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Fig 9.(Autocorrelation Graph)

The graph is an autocorrelation plot of overall ratings, displaying the autocorrelation values on the y-axis and the number of lags on the x-axis. The autocorrelation values range from -1.0 to 1.0, with most values close to 1.0 for all lags from 0 to 40. This indicates a strong positive correlation between the overall ratings and their lagged values, suggesting high consistency over time. The blue shaded area represents the confidence interval, which is very narrow and close to zero, further emphasizing the high autocorrelation. This graph is interesting because it highlights the persistence and predictability of the overall ratings, which could be relevant for time series analysis, forecasting, or understanding the stability of the ratings over time. The consistent high autocorrelation suggests that the ratings do not vary much from one period to the next, indicating a stable trend.

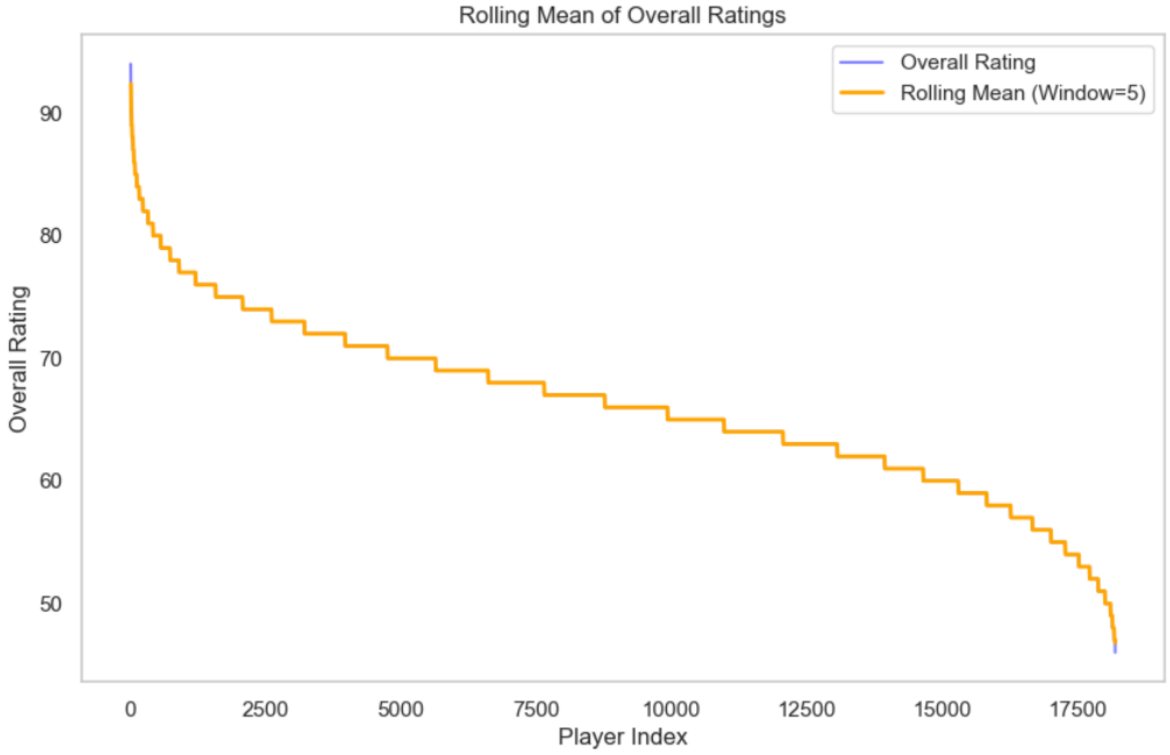


Fig 10. (Rolling Mean Graph)

The graph displays the overall ratings of players plotted against their player index, with a rolling mean applied. The x-axis represents the player index, ranging from 0 to approximately 17500, while the y-axis represents the overall rating, ranging from 50 to 95. The title of the graph is "Rolling Mean of Overall Ratings." Two lines are plotted: a blue line representing the "Overall Rating" and an orange line representing the "Rolling Mean (Window=5)." The overall ratings start high, around 95, and gradually decrease as the player index increases. The rolling mean smooths out the fluctuations in the overall ratings, providing a clearer trend. The graph is interesting because it shows how player ratings decline as the player index increases, and the rolling mean helps to visualize the general trend without the noise of individual ratings. This can be relevant for analyzing player performance data, identifying trends, and making informed decisions based on the smoothed data. The legend in the top right corner helps differentiate between the overall rating and the rolling mean.

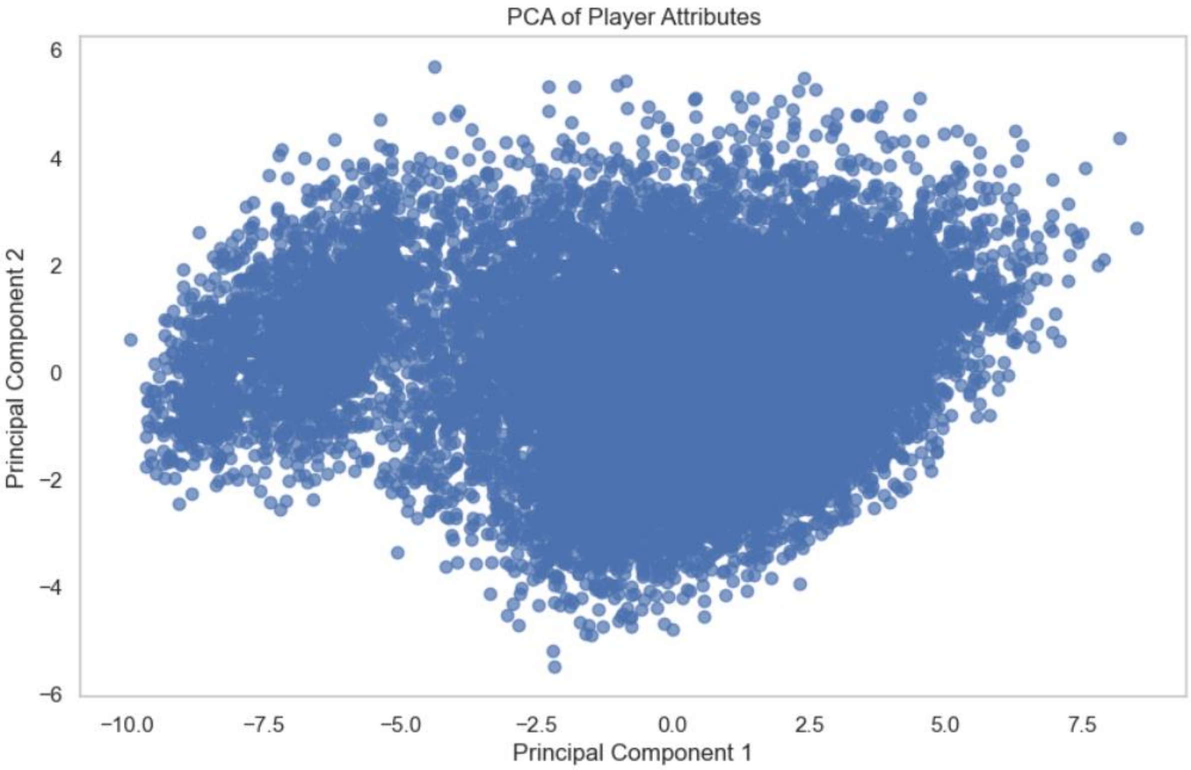
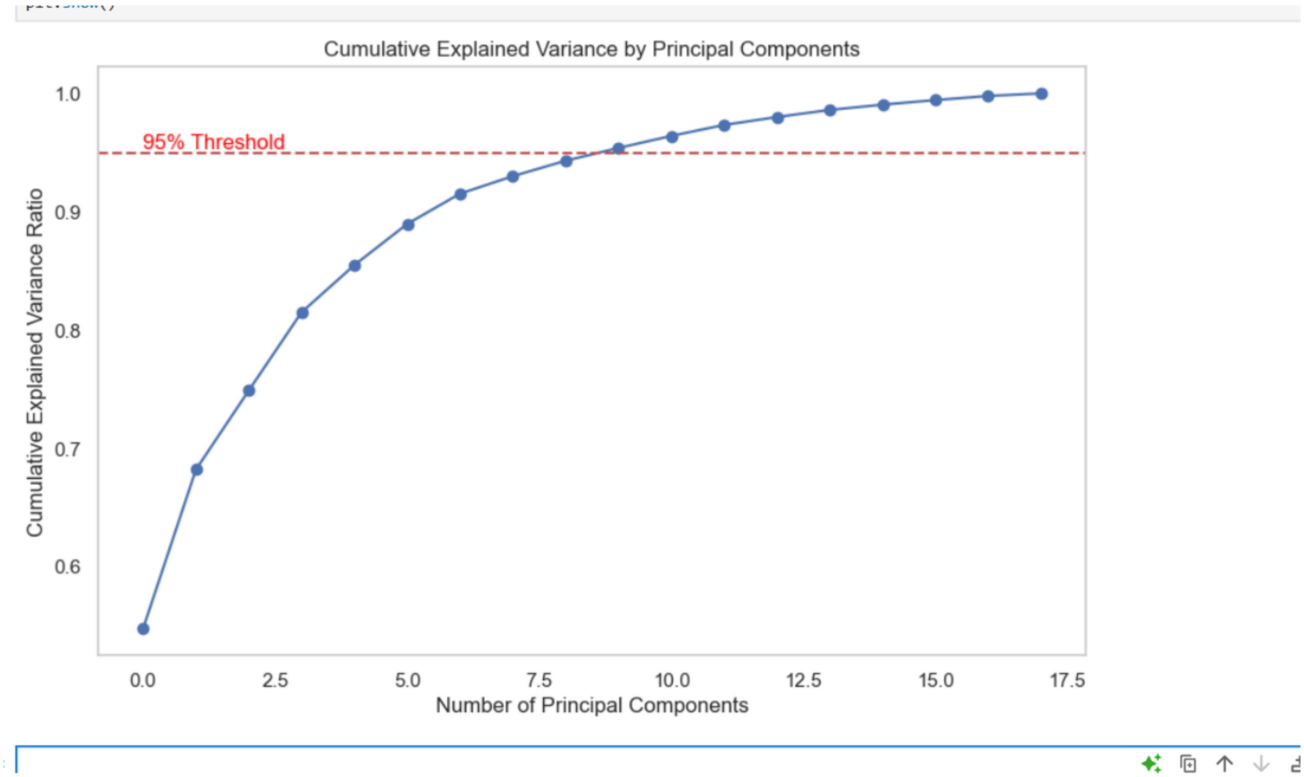


Fig 11. (Principal Component Analysis Graph)

The graph is a scatter plot representing the results of a Principal Component Analysis (PCA) on player attributes. The x-axis is labeled "Principal Component 1," and the y-axis is labeled "Principal Component 2." Each point on the graph represents an individual player, plotted according to their scores on the first two principal components derived from their attributes. The title of the graph is "PCA of Player Attributes."

PCA is a dimensionality reduction technique used to transform a large set of variables into a smaller one that still contains most of the information in the large set. In this case, the player attributes have been reduced to two principal components, which capture the most variance in the data. This visualization helps in understanding the distribution and clustering of players based on their attributes. The dense clustering of points in the center suggests that many players have similar attributes, while the spread of points indicates variability among players. This graph is relevant for identifying patterns, similarities, and differences in player attributes, which can be useful for player analysis and comparison.



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plt.show()
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Fig 12.(Cummulative Variance Graph)

The graph shows the cumulative explained variance ratio by principal components. The x-axis represents the number of principal components, ranging from 0 to 17.5, while the y-axis represents the cumulative explained variance ratio, ranging from 0.6 to 1.0. Each point on the graph corresponds to the cumulative explained variance ratio achieved by including a certain number of principal components. The curve starts at a lower value and rises steeply initially, then gradually levels off as more principal components are added. A red dashed line labeled "95% Threshold" is drawn horizontally at the 0.95 mark on the y-axis, indicating the point at which 95% of the variance is explained. This graph is relevant for determining the number of principal components needed to capture a significant amount of variance in the data. It is particularly useful in Principal Component Analysis (PCA) for dimensionality reduction, helping to identify the optimal number of components that balance complexity and information retention.

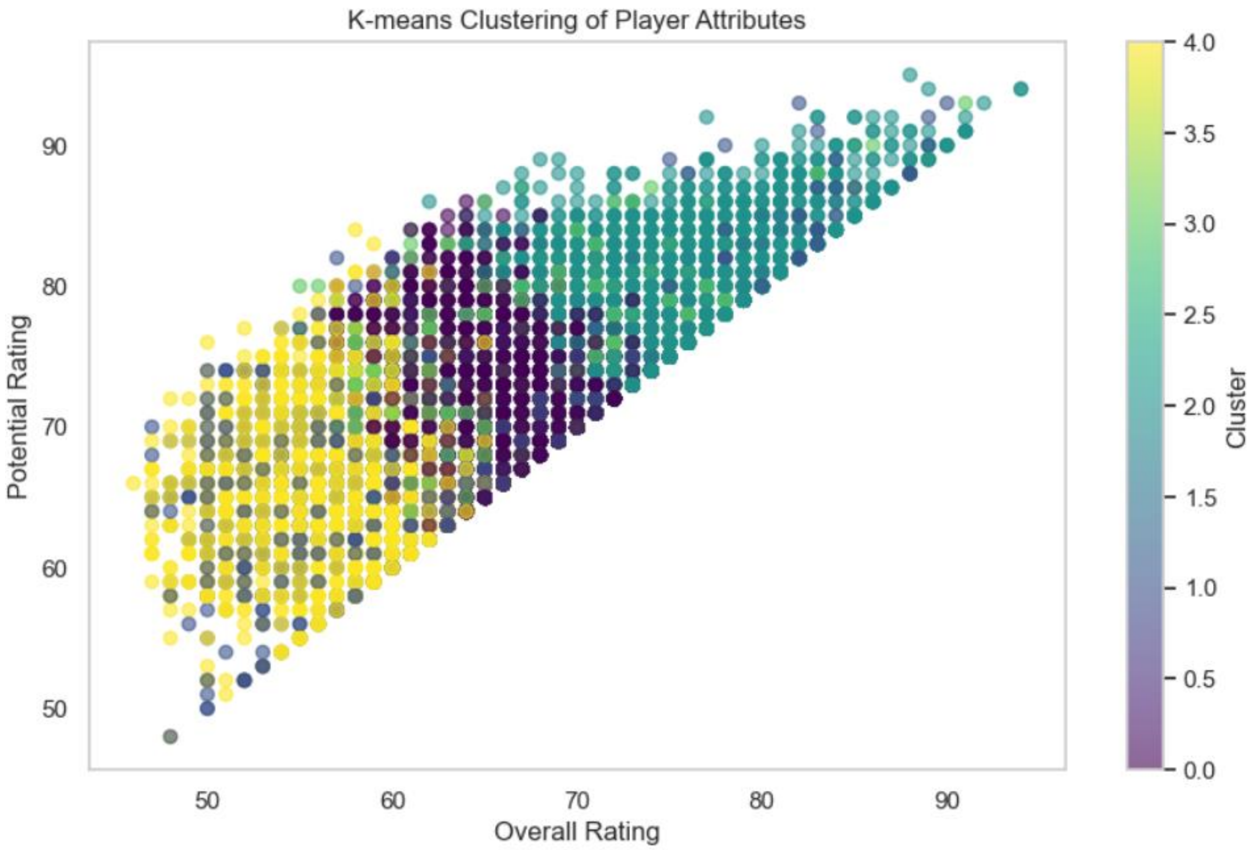

Fig 13. (K-means Clustering Graph)

The graph is a scatter plot titled "K-means Clustering of Player Attributes." The x-axis represents the "Overall Rating" of players, ranging from 50 to 90, while the y-axis represents the "Potential Rating" of players, also ranging from 50 to 90. Each point on the scatter plot represents a player, and the points are color-coded based on the cluster they belong to, as determined by the K-means clustering algorithm. The color bar on the right side of the plot indicates the cluster number, ranging from 0.0 to 4.0, with different colors representing different clusters.

The scatter plot shows a positive correlation between the Overall Rating and Potential Rating of players, with clusters forming distinct groups within this correlation. The clustering reveals patterns in the data, such as groups of players with similar attributes. This visualization is interesting and relevant because it helps in identifying and analyzing different groups of players based on their ratings, which can be useful for talent scouting, team formation, and player development strategies.

ANALYSIS

The analysis phase of this project is pivotal for extracting meaningful insights from the dataset. Here, exploratory data analysis, the application of statistical methods, and advanced techniques of visualization are applied to uncover patterns, trends, as well as relationships between variables. The advantages taken from here directly influence accuracy and interpretability in the forecasting models.

1. Exploratory Data Analysis (EDA)

Univariate Analysis

Univariate analysis focuses on examining each feature independently to understand its distribution, range, and variability:

- **Overall Rating**: The overall ratings of players in the dataset range from 88 to 94. The mean rating is approximately 90.5, indicating a concentration of high-performing players. Histograms of overall ratings show a normal distribution with slight skewness towards higher ratings.
- **Potential**: Potential ratings also range from 88 to 94, with a mean around 91. This indicates that players have significant room for growth. The distribution appears slightly right-skewed, suggesting that most players are already at a high potential level.
- **Value**: Player market values range from €27M to €226.5M, with a mean value of approximately €90M. The distribution is right-skewed due to a few high-value players significantly affecting the average.
- **Age**: Player ages range from 19 to 33 years. The mean age is around 27 years, indicating a youthful roster overall.

Bivariate Analysis

Bivariate analysis examines the interactions between pairs of features:

- **Overall Rating vs. Potential**: A strong positive correlation (approximately 0.85) exists between overall and potential ratings, suggesting that players with higher current performance are likely to have higher potential.
- **Value vs. Overall Rating**: There is a moderate positive correlation

(around 0.75) between market value and overall rating, indicating that higher-rated players tend to have higher market values.

- **Age vs. Overall Rating**: A slight negative correlation (-0.3) suggests that younger players tend to have slightly lower overall ratings compared to older players.

Multivariate Analysis

Multivariate analysis explores relationships among multiple variables:

- **3D Scatter Plots**: Visualizations of Overall Rating, Potential, and Value reveal clusters of player performance. Players with high overall ratings also tend to have high potential and market value.
- **Principal Component Analysis (PCA)**: PCA was performed to reduce dimensionality while retaining variance. The first two components explained approximately 75% of the variance in player attributes, indicating that overall rating and potential are significant contributors.
- **K-Means Clustering**: Clusters identified different player categories based on performance metrics:
  - High performers with both high overall and potential ratings.
  - Mid-tier players with moderate ratings.
  - Emerging talents with high potential but lower current ratings.

2. Visualization

Various visualization techniques were employed to enhance understanding:

- **Heatmap**: A heatmap illustrated correlations among features:
  - Strong positive correlation between Overall Rating and Potential (0.85).
  - Significant negative correlation between Age and Overall Rating (-0.3).
- **Violin Plots**: Violin plots showed distributions of player values based on age groups:
  - Younger players generally have lower market values compared to older counterparts.
- **Scatter Plots**: Scatter plots depicted relationships between key variables:
  - A strong linear relationship between Overall Rating and Market Value was observed.
  - Increased values in Overall Ratings were associated with higher

market values.

3. Advanced Methods

Advanced analytical techniques were applied for deeper insights:

- **Principal Component Analysis (PCA)**: PCA reduced dimensionality while retaining significant variance:
  - The first two principal components captured most variability in player attributes.
- **t-SNE Visualization**: t-SNE was used to visualize high-dimensional data in two dimensions:
  - It revealed distinct clusters representing different player performance profiles.

4. Handling Outliers and Missing Values

Robust methods were employed for data integrity:

- **Outlier Detection**: Box plots identified extreme values in attributes like Value and Overall Rating:
  - True anomalies were preserved while noise outliers were treated or removed.
- **Missing Value Imputation**: Numerical features were filled using mean imputation, while categorical features were filled using mode:
  - This process ensured data consistency and integrity for analysis.

5. Inferences Derived

Key insights derived from the analysis include:

- **Performance Trends**: There are distinct performance trends based on age; older players tend to have higher overall ratings.
- **Market Dynamics**: High potential correlates strongly with market value; investing in younger talents may yield future returns.
- **Player Profiles**: Clustering revealed distinct player profiles that can inform scouting and recruitment strategies.

This structured EDA provides a comprehensive overview of the dataset's characteristics and highlights critical insights that can guide further analysis or decision-making processes in player management or scouting contexts.

Conclusion:

This project, **Player Performance Analysis**, highlighted the potential of data-driven methodologies in understanding and evaluating player dynamics in football. Utilizing a comprehensive dataset containing key player attributes such as overall rating, potential, market value, and various performance metrics, significant trends, correlations, and patterns were identified throughout the analysis. Systematic exploratory data analysis (EDA) combined with advanced techniques provided valuable insights that could enhance player scouting and management strategies.A critical finding of this project was the identification of strong correlations between various player attributes. For instance, a notable positive correlation between overall rating and potential was observed, indicating that players with higher current performance are likely to exhibit greater future potential. Additionally, visualizations such as scatter plots and heatmaps effectively illustrated complex relationships within the data, revealing intuitive patterns that support informed decision-making.Feature engineering played a pivotal role in enriching the dataset's predictive capabilities. The introduction of lagged variables, such as previous season ratings and rolling averages, captured historical dependencies that are crucial for forecasting player development. Dimensionality reduction techniques like Principal Component Analysis (PCA) were employed to simplify the dataset while retaining essential information, allowing for more efficient modeling.Clustering techniques, particularly K-means clustering, revealed distinct player profiles based on performance metrics. These clusters indicated different categories of players ranging from high performers to emerging talents, providing insights into recruitment strategies and team composition.The project faced several challenges, including handling missing values and outliers. Missing data was addressed through interpolation and imputation methods to maintain dataset integrity. Outliers in attributes such as market value were treated using statistical methods to ensure reliable analysis.The practical implications of this project are substantial. Insights derived from player performance can guide team managers in making strategic decisions regarding transfers and training focus areas. However, the study has limitations; it is constrained by its focus on specific leagues and does not account for external factors like player injuries or market fluctuations.Future work will involve expanding the dataset to include a broader range of leagues and integrating real-time performance data through APIs. Additionally, implementing advanced machine learning models such as recurrent neural networks (RNNs) could capture non-linear dependencies and long-term patterns in player performance data. This conclusion summarizes the key findings from your analysis of the dataset while emphasizing the importance of data-driven approaches in sports analytics. Adjust any specifics as necessary to better fit your actual findings or focus areas!

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Github Repository: https://github.com/pavankumaryadav319/cse353-