Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

Stacked Ensemble-Based Framework for Predicting Market and Tactical Fit in Football Transfers

Submitted in partial fulfillment of the requirements of the degree of

Bachelor of Technology

In

Artificial Intelligence (AI) and Data Science

By,

Vedant Bhawnani	**60018210069**
Shubh Harde	**60018220135**

Under the guidance of
Prof. Shruti Dodani
Dwarkadas J. Sanghvi College of Engineering

UNIVERSITY OF MUMBAI

ARTIFICIAL INTELLIGENCE (AI) AND DATA SCIENCE DEPARTMENT

CERTIFICATE

This is to certify that, the project entitled "**Stacked Ensemble-Based Framework for Predicting Market Value and Tactical Fit in Football Transfers**" is a bonafide work of Vedant Bhawnani(60018210069) and Shubh Harde(60018220135) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of B.Tech. in Artificial Intelligence (AI) and Data Science.

Prof. Shruti Dodani

Internal Guide **External Examiner**

Dr. Pratik Kanani Dr. Hari Vasudevan

Head of Department **Principal**

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Project Report Approval

This project report entitled "**Stacked Ensemble-Based Framework for Predicting Market Value and Tactical Fit in Football Transfers**" by Vedant Bhawnani, Shubh Harde is approved for the degree of B.Tech. in Artificial Intelligence (AI) and Data Science Engineering.

Examiners

1) ………………………………..

2) ………………………………..

Date:

Place:

Declaration

We declare that, this written submission represents our ideas in our own words and where others' ideas or words have been included, We have adequately cited and referenced the original sources. We also declare that, We have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

1) Shubh Harde – 60018220135

2) Vedant Bhawnani - 60018210069

Date:

Abstract

The transfer markets in football are a dynamic and pivotal period which entails a state of volatility where teams and clubs strategize and aim to strengthen their teams. This is more often than not preceded by in-depth analysis of data related to hundreds of promising and prospective players to find the perfect replacement for the outgoing player. This analysis currently includes labour-intensive tasks of manual video reviews and scouts going to games to watch a prospect play. This research introduces the Football Player Replacement Finder, a novel approach to reduce the complexity and time required for scouting and acquiring impactful talents by using advanced machine learning models and automated data scraping pipelines. Our system employs supervised models for gauging the performance and price of football players along with clustering techniques for player profiling, enabling stat-by-stat comparison of players. By integrating advanced metrics along with appealing visualisations, our system empowers decision-makers to streamline their scouting process and uncover valuable talents effectively.

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Chapter 1

Introduction

1.1 Description

One of the most important periods for any football team trying to bolster their roster is the transfer window, particularly in January and July. Clubs put a lot of effort into scouting possible additions during these months, while simultaneously monitoring players who might depart. Finding qualified replacements without going over budget is crucial for clubs since maintaining financial stability is a top concern. A thorough examination of a number of variables, including player statistics, market trends (such as inflation and volatility), team dynamics when adding a new player, and even possible conflicts in player personalities, is necessary to scout individuals while making sure they match the budget.

This procedure has historically taken a long time and involved reviewing a lot of video footage, compiling subjective reports, and manually comparing statistics. It's getting harder for contemporary football teams to stay up to date with these outdated techniques as more data becomes available and measurements get more complex.

1.2 Problem Formulation

The issue is that many football teams continue to employ antiquated and time-consuming scouting techniques. Despite the abundance of player data and statistics provided by systems such as FBref and Sofifa, the present method of identifying appropriate substitutes still mostly depends on manual comparisons and subjective judgements. These conventional techniques just cannot keep up with the volume and complexity of contemporary player scouting as more data becomes available.

Furthermore, depending solely on subjective reports may result in biases in player evaluations and the omission of important information regarding player performance. Clubs also face the onerous task of identifying replacements who meet the team's tactical requirements and budget, which is hard to handle by hand.

1.3 Proposed Solution

This study aims to streamline and modernize the recruitment and replacement process, by incorporating machine learning and automating data analytics. The system can find players who are statistically comparable to the one being replaced and anticipate player performance using machine learning methods, such as supervised machine learning and clustering algorithms. To make sure that the comparison between players is as precise and pertinent as feasible, it makes use of similarity metrics including cosine similarity, Pearson correlation, and Euclidean distance.

Implementing automated data scraping lets us quickly collect player performance data from online sources, including FBref and TransferMarkt. The system focuses specifically on the statistical performance of a player, things like expected goals, assists, and passing accuracy. This process removes the manual efforts and potential biases found in conventional scouting, allowing scouts to focus on other things. It ensures player comparisons are faster, more objective, and grounded purely in performance indicators.

Clubs can use this technique to make better-informed decisions regarding possible acquisitions, guaranteeing that new players meet the team's long-term objectives as well as its immediate tactical requirements.

1.4 Scope of the Project

This project aims to deliver a one-stop tool for scouting and team management. Its purpose is to assist in uncovering hidden talent and discovering players suited to a team's style. The system will also use similarity measures on online data to evaluate and find replacements for departing players. Emphasis is placed solely on on-field metrics that align directly with a team's requirements.

The project will not, however, address the broader aspects of football management, such as contract negotiations, off-field player conduct, or psychology. Unless there is a direct impact of an action on a player's performance, such as injury records, the system will not take non-performance characteristics into consideration. In the end, the technology is aimed to offer precise player comparisons and recruiting forecasts, leaving the club's management staff to gauge how well a player fits in their club dynamics.

Chapter 2

Review of Literature

The estimation of football players' market value has been an area of extensive research, with scholars utilizing a variety of methods, datasets, and algorithms to improve the how accurately the models can predict these values . This section provides a detailed literature review focusing on the application of machine learning and deep learning techniques for player valuation. Several studies have identified the key factors that most influence the market value. Among these, age emerges as a crucial deciding factor, as younger players are often valued higher due to their developmental potential. Additionally, a player's popularity can elevate their market worth, as it is commonly associated with increased fan engagement and commercial appeal [1]. The player's on-field position is another crutial factor. Attackers, in particular, are generally attributed higher market values [2].

The use of regression models to determine the factors influencing football transfer fees was first introduced by Carmichael and Thomas (1993) [3]. Building on their approach and research, many further studies adopted the regression-model in the sports and analysis domain. Building on this tradition, Mustafa and Al-Asadi utilized FIFA data as a benchmark for actual market values and applied both linear and non-linear models to estimate player prices [4]. Their methodology incorporated nine distinct parameters, including international reputation and the "weak foot" attribute, among others.

Stanojevic and Gyarmati conducted a study utilizing statistical methods, sourcing their data from the sports analytics firm InStat and the publicly available platform Transfermarkt [5]. Adopting a conventional methodology, their research aimed to estimate the market value of 12,858 football players based on various performance indicators. They employed clustering techniques to interpret player performance data and developed a model using 45 predictor variables. The resulting estimates demonstrated better accuracy compared to the widely accepted market values provided by Transfermarkt, highlighting the potential of advanced data analytics and granular performance metrics in enhancing valuation precision [6].

Müller et al. [1] proposed a data-driven methodology to tackle the limitations of crowd-sourced market value estimates. Their study utilized data from the top five European football leagues and constructed a comprehensive dataset incorporating player-specific attributes such as age, position, and nationality. Notably, their approach also integrated supplementary data from external sources, including Wikipedia, Facebook, and Google metrics, reflecting public interest and online presence. A linear regression model was employed to estimate player market values, and the results aligned closely with existing crowd-sourced valuations, demonstrating the viability of their approach.

Dobson et al. [7] examined the influence of player-specific metrics on transfer fees and observed significant volatility in transfer valuations, even within the same competitive league. Expanding on this line of inquiry, more recent work by Depken II and Globan employed linear regression analysis to demonstrate that English football clubs tend to pay a premium for players in the transfer market compared to their counterparts from other European nations.

Yigit et al. introduced an innovative methodology for estimating player market values by utilizing a broad spectrum of player attributes, including on-field performance metrics, demographic characteristics, and market-related factors. Their dataset encompassed 5,316 players from 11 prominent football leagues in Europe and South America. The study achieved market value predictions close to the actual transfer market values by integrating data from the Football Manager simulation game alongside transfer value data sourced from Transfermarkt.[8].

In a distinct approach, Behravan et al. applied Particle Swarm Optimization (PSO) to predict player market values, using data from the FIFA 20 dataset, where the in-game player value was considered the true market value. They employed an automatic clustering algorithm to categorize players into four clusters based on their positions. Their method demonstrated superior performance, with RMSE and MAE values of 2,819,286 and 711,029,413, respectively, compared to the results obtained by Müller et al. [6], which had RMSE and MAE values of 5,793,474 and 3,241,733. These results underscore the effectiveness of their approach in predicting market values more accurately [9].

Ian et al. [10] used machine learning techniques to estimate football transfer fees, using data from sofifa.com and transfermarkt.com. They trained both linear regression and XGBoost models on a variety of performance metrics, including data from Instat and GIM performance ratings. Their results showed that the XGBoost model outperformed the linear regression model in predicting transfer fees. This study underscores the potential of machine learning to enhance transfer decision-making, specifically in answering the question, "What is the expected transfer fee of a player based on their previous performance?" The authors also propose further research to evaluate the "reasonableness" of transfer fees by considering post-transfer performance, publically available data sources, and potentially applying similar machine learning methods.

Chapter 3

System Requirements Specification

3.1 Introduction

3.1.1 Aim

This section lays out the blueprint for the Football Player Replacement Finder system. Detailed here is what the system needs to do (its functions) and how well it needs to do it (its qualities). The core idea is to give football clubs, their scouts, and analysts a one-stop tool. By utilizing data analytics and machine learning, this approach aims to increase the accuracy and efficiency of finding possible replacement players.

3.1.2 What this covers

The Football Player Replacement Finder system is designed to handle several key tasks. It automatically gathers player performance statistics, market information, and player demographics from public websites like FBref and Transfermarkt. The system then combines this data, cleaning up inconsistencies to build a single, consistent player dataset. It generates detailed player profiles, including performance numbers, estimated market value, and personal details. These profiles are enhanced by adding feature-engineered metrics specific to different on-field roles. When a player leaves a club, the system finds and ranks potential replacements by evaluating statistical similarity, playing style, and other criteria set by the user. Finally, the system presents all this information through an easy-to-use interface featuring helpful visualizations, aiding scouts in decision-making.

Our primary focus is on a player's on-field performance and how it aligns with a team's needs. We are not including areas like contract terms, in-depth player psychology, off-field conduct, or comprehensive injury logs in the system. These are outside the system's scope, unless an injury directly impacts the core on-field statistics obtained from our sources. Similarly, the system does not provide real-time match analysis or use live data feeds; it updates its data periodically by checking the defined online sources.

3.1.3 Overview

This remainder of this section is structure as follows: Section 3.2 provides the an overview – its main functions, who'll be using it, and significant limitations or dependencies. Then, Section 3.3

details exactly what the system must do, how well it must perform, and how it interacts with the outside world.

3.2 System Overview

3.2.1 Product Goal

The Football Player Replacement Finder is aimed to be a dedicated tool to aid decision-making within football scouting departments. While it operates as a self-contained system, it depends heavily on the data drawn from publicly accessible online platforms. In its current form, it's not designed to plug directly into existing club management software, but rather to deliver actionable intelligence that can then be manually woven into a club's operational workflows. Though it stands on the shoulders of established data analytics concepts and machine learning approaches tailored for the football world, it is a fresh product aimed to be an aid to the scouts in the decision-making process.

3.2.2 Core Functions

The Football Player Replacement Finder will handle several key responsibilities:

- Automatically fetch data from the defined football statistics websites.
- It's designed to build up thorough player profiles, looking at both raw stats and underlying playing styles.
- A core capability will be its intelligent suggestions for similar players, especially useful when a replacement is needed.
- The system will also contain predictive models to give an estimate of a player's market value.
- All this will be accessible through a user-friendly interface designed for easy data exploration and clear visualization of football analytics.

We'll break these down in much more detail in Section 3.3.1.

3.2.3 Target Users

This system is designed while keeping the following roles and people in mind:

- **Football Scouts and Analysts:** These are the frontline professionals tasked with assessing players. We expect them to know football inside out, but their tech-savviness might vary.

The system needs to be approachable even for those not deeply versed in complex data tools.

- **Team Managers/Coaches:** They might use the system to get a clearer picture of player profiles or to double-check scouting insights.
- **Sports Data Aficionados/Researchers (Secondary Audience):** We also foresee individuals using the system for academic pursuits or personal explorations into player data.

Providing only a web interface is intentional since the target audience might not be tech-savvy, hence a web interface with provide the least resistance to use.

3.2.4 Operational Boundaries and Limitations

The quality of the system's insights defend on the accuracy and ongoing availability of data. This said, in the future the model should be retrained to take into account the inflation and market trends. The data gathering should be done systematically, following the guidelines of the website being scraped, and pipelines being run on the said data.

The initial goal of the project is focused only on the men's professional football leagues, though the use case of this project can be extended into different sports with relevant and high quality data. The system is built to run on everyday desktops and laptops, as detailed in section 3.3.4.

3.2.5 Key Assumptions and Dependencies

We're proceeding with a few assumptions in mind:

- That the public football data sites we rely on (FBref, Transfermarkt, etc.) will continue to be accessible, and their basic structure won't change so drastically as to completely break our data collection methods without warning.
- Users will need a stable internet link for the system to fetch fresh data.

3.3 Detailed System Requirements

3.3.1 Functional Requirements

Here, we spell out the precise actions and capabilities of the system. Each function gets a unique tag (FR.x) for easy reference.

3.3.1.1 FR.1: Managing the Data Flow

- **FR.1.1 (Fetching Data Automatically):** The system is required to automatically pull player statistics, market information (including past values if gettable), and demographic details from our specified web sources (FBref, Transfermarkt).
- **FR.1.2 (Combining Data Together):** The system must be capable of merging data from these diverse sources. This involves cleaning it up, transforming it as needed, and sorting out any discrepancies (like different ways player names are spelled) to produce one consistent player dataset.
- **FR.1.3 (Maintaining Data Standards):** There needs to be a way for the system to update its player database with the newest information from our sources, either when a user triggers it or on a set schedule.

3.3.1.2 FR.2: Analysing and Profiling Players

- **FR.2.1 (Building Player Sections):** For every player, the system will construct a thorough profile. This section will show key performance indicators (KPIs), data about their position(s), contract details (where available), and basic demographic info.
- **FR.2.2 (Metrics by Position):** The system needs to calculate and show specialized, derived stats that are tailored to different roles on the field (e.g., how many Shots are Saved per 90 minutes for Keepers, or Progressive Passes per 90 for Midfielders).

3.3.1.3 FR.4: Forecasting Market Value

- **FR.4.1 (Model Readiness):** The system will provide a Stacked Ensemble model, trained on the data available during the last training of the model to predict the market value of a player.
- **FR.4.2 (Showing Predictions):** For every player, the system will display its predicted market value. This will sit alongside their actual market value (if we have it from our sources) and, some indication of its typical error margin, using the R^2 score.

3.3.1.4 FR.5: Interface and Visuals

- **FR.5.1 (Dynamic Dashboards):** The system will feature interactive dashboards that show player data in an intuitive fashion. This means things like radar charts for comparing player attributes, and showing calculated metrics to deep dive into a player's football psychic.

- **FR.5.2 (League-Level Insights):** Users should be able to pick a league and then see visual summaries of league standings, team stats, and leader boards for top players (like top scorers or assist providers), among other relevant league-wide information.
- **FR.5.3 (Easy Navigation):** The User Interface (UI) has to be straightforward. Users should find it easy to search for players, apply filters and navigate the other features the UI offers.
- **FR.5.4 (System Feedback):** The UI needs to keep the user in the loop, especially when data is being loaded or processed, by being responsive and providing clear feedback.

3.3.2 How the System Should Perform: Non-Functional Requirements

This part specifies the quality benchmarks for the system.

3.3.2.1 NFR.1: Speed and Responsiveness

- **NFR.1.1 (Quick Lookups):** Basic player searches and pulling up a player's profile should happen fast.
- **NFR.1.2 (Efficient Data Gathering):** Full cycles of scraping data or updating it should be done in a sensible amount of time(a few hours, this will depend heavily on the network and deployment server constraints) and must be "polite" to the source websites (e.g., not hammering them with too many requests too quickly).

3.3.2.2 NFR.2: Ease of Use

- **NFR.2.1 (Short Learning Curve):** Someone new to the system, but who understands football, should be able to get the hang of core tasks (like finding a replacement or viewing a profile) with very little fuss – possibly with no formal training.
- **NFR.2.2 (Clear Visuals):** All charts, graphs, and any other visual ways data is presented must have clear labels and be easy to understand at a glance.
- **NFR.2.3 (Preventing and Handling Mistakes):** Where possible, the system should stop users from entering invalid data. When mistakes do happen, it needs to provide clear messages that help the user fix the problem.

3.3.2.3 NFR.3: Dependability

- **NFR.3.1 (Resilient Data Scrapers):** The bits of code that grab data from websites should be built to cope with small changes in how those websites are laid out. Big changes might still need code updates, though.

- **NFR.3.2 (Availability - If Online):** If we deploy this as a web service, we'd aim for it to be up and running 99.5% of the time. (This doesn't apply if it's just a desktop app).
- **NFR.3.3 (Keeping Data Safe):** The system must make sure the data it stores is kept intact, preventing it from getting corrupted or accidentally lost.

3.3.2.4 NFR.4: Maintainability and Scope of Growth

- **NFR.4.1 (Built in Modules):** The system should be put together in a modular way (e.g., data scraping, machine learning models, and the user interface should be somewhat separate parts).
- **NFR.4.2 (Well-Commented Code):** Informational comments should be added to key parts of the code, especially the tricky sections like algorithms and how data is processed, to explain what is going on.
- **NFR.4.3 (Easy to Tweak):** Things like website addresses for data sources, settings for the machine learning models (where it makes sense), and how often data is scraped should be adjustable without having to rewrite the code itself.

3.3.2.5 NFR.5: Accuracy

- **NFR.5.1 (Data Quality):** The data scraped should be a true reflection of what's on the source websites at the moment it was collected.
- **NFR.5.2 (Good Predictions):** The model that predicts market values should hit a certain target for accuracy – for instance, an R-squared value better than 0.85 when tested on data it hasn't seen before, and a minimal difference when comparing the R-squared value between the train and test datasets.

3.3.3 Interacting with the Outside World: External Interfaces

3.3.3.1 User Interfaces

The system will feature a Graphical User Interface (GUI). The look and feel, along with key user journeys, are shown in our UI design screenshots (you can find these in Chapter 4, under the User Interface Design section).

3.3.3.2 Connections to Hardware

No specialized or custom hardware connections are needed. The system is designed to run on standard desktop or laptop computers.

3.3.3.3 Connections to Other Software

- For data scraping, the system will connect to external websites (FBref, Transfermarkt, Sofifa) using standard web protocols (HTTP/HTTPS).
- The system will lean on several Python libraries for its heavy lifting: Pandas and NumPy for data wrangling, Scikit-learn and XGBoost for machine learning, and Matplotlib, Seaborn, or Plotly for creating visualizations.

3.3.3.4 Network requirements

An active internet connection is a must for the system to scrape data from online sources. It will use the usual web protocols (HTTP/HTTPS) to communicate between the user's browser and the server where it is deployed.

3.3.4 Specific Requirements

We are targeting an audience that may or may not own specialized hardware, and have kept the necessary requirements at a minimum. A everyday computer or laptop with a decent network connection should be able to access websites. To replicate the work denoted here, the minimum requirements are a laptop with atleast 8GB RAM, sufficient hardware space, and a fast network connection. Having a dedicated GPU would be beneficial in training the machine learning model.

3.4 Use Case Description

This section breaks down the primary ways users will interact with the system.

3.4.1 Target Audience

- **Scout/Analyst:** This is our intended target audience. They'll be interacting with the system to assess players and find suitable replacements.

3.4.2 Use Case Descriptions

3.4.2.1 UC.1: Examining a Player's Detailed Profile

Name: Review Player Dossier

Goal in Context: The Scout/Analyst aims to gain a comprehensive understanding of a specific player by viewing their detailed statistical information, performance metrics, and associated visualizations.

Preconditions:

- The system has player data available.
- The Scout/Analyst has selected a specific player for review.

Trigger: The Scout/Analyst navigates to a player's profile page or selects a player from a list.

Main Success Scenario:

1. The Scout/Analyst selects a player.
2. The system retrieves and displays the player's detailed profile, including:
    - Basic information (age, nationality, position, club).
    - In-depth performance statistics (goals, assists, passing accuracy, defensive actions, etc., relevant to their position).
    - Advanced metrics (xG, xA, progression stats).
    - Visualizations of performance (e.g., radar charts, performance graphs over time).
    - Comparison with similar players or league averages (if applicable).
3. The Scout/Analyst reviews the information.

Extensions (Alternative Flows):

- **2a. Player Data Incomplete:** If some specific metrics are unavailable for the player, the system displays available data and indicates missing information.
- **2b. Comparison Requested:** The Scout/Analyst initiates a direct comparison with another player from the profile view.

Postconditions:

- The Scout/Analyst has a detailed understanding of the player's capabilities and performance profile.
- The Scout/Analyst may add the player to a shortlist or take notes.

3.4.2.2 UC.2: Assessing League-Wide Data and Trends

Name: Analyze League Landscape

Goal in Context: The Scout/Analyst wants to review aggregated statistics, current standings, and identify top-performing players within a chosen football league.

Preconditions:

- The system has league data available (standings, team stats, player stats).
- The Scout/Analyst has access to the league analysis section.

Trigger: The Scout/Analyst selects a specific league to analyze.

Main Success Scenario:

1. The Scout/Analyst chooses a football league from the available options.
2. The system retrieves and displays a league dashboard, including:
   - Current league standings table.
   - League-wide aggregated statistics (e.g., average goals per game, possession stats).
   - Lists of top performers in key categories (top scorers, top assisters, most clean sheets).
   - Visualizations of team performance comparisons (e.g., attack vs. defense scatter plots).
3. The Scout/Analyst reviews the league overview and identifies trends or standout teams/players.

Extensions (Alternative Flows):

- **3a. Drill-down to Team/Player:** The Scout/Analyst clicks on a team or player from the league dashboard to view their detailed profile (linking to UC.2 or a similar team use case).
- **3b. Filter/Sort Data:** The Scout/Analyst applies filters (e.g., by date range, specific stats) or sorts leader boards.

Postconditions:

- The Scout/Analyst has a better understanding of the competitive landscape of the selected league.
- Potential scouting targets or areas of interest within the league may be identified.

Chapter 4

Analysis Modeling

4.1 Time Line Chart

The proposed system was developed in the final year of B.Tech, covering the span of August '24 - April '25. This includes the time taken for project ideation and project execution. A detailed chart showing the timeline of the project is shown below in figure :

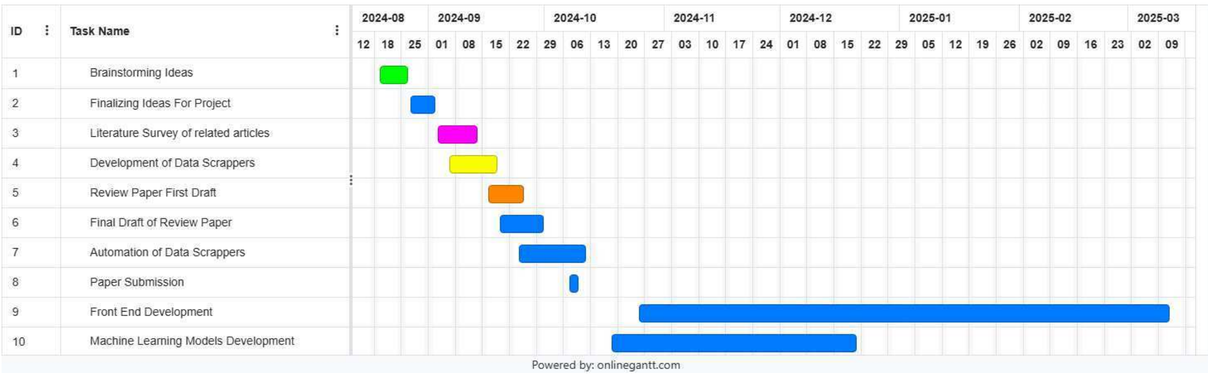


Figure 1: Timeline chart

Chapter 5

Design

5.1 Proposed Design

The proposed system uses advanced on-field player performance metrics, domestic and continental performance of football clubs, players perceived market value, player injury data and domestic competition metrics like standings and top performers. The data is collected from FBref and Transfermarkt using automated web scraping scripts. The collected data is put through a data processing pipeline which cleans and transforms the data to match the needs of the system. The preprocessed data is used by machine learning models for calculating consolidated metrics for comparing players Fig. 1. Proposed Methodology and teams, determining similar players, formation fit analysis and market price prediction. Figure 1 shows the proposed methodology.

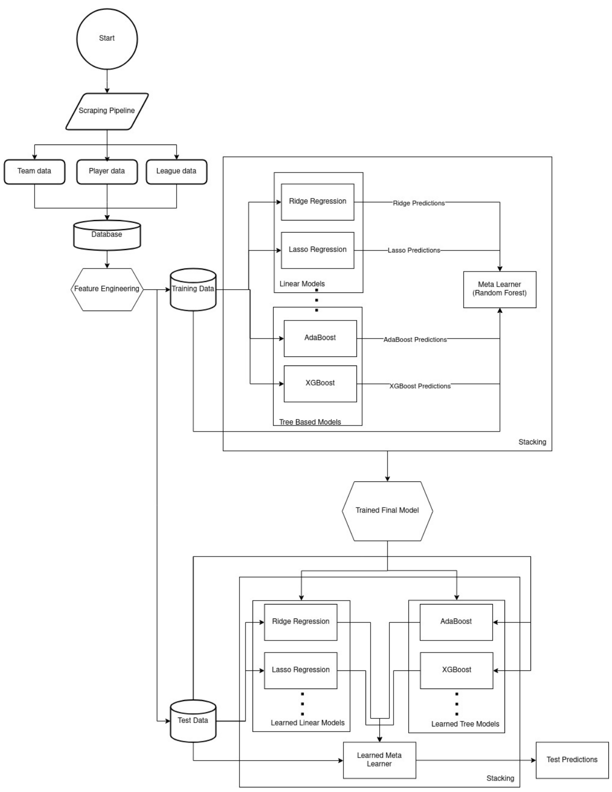


Figure 2: Proposed Model Architecture

5.2 User Interface Design

This section details the design and workflow of the application's user interface (UI). The UI was designed to facilitate intuitive navigation and efficient data exploration for users. The process is presented through a series of screenshots, demonstrating a typical user journey from the application's entry point to key functional areas.

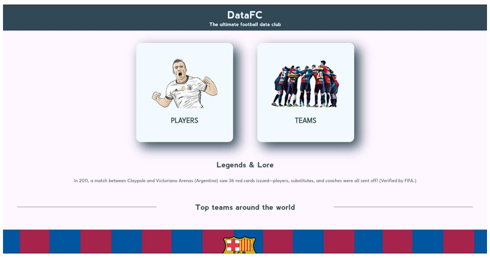
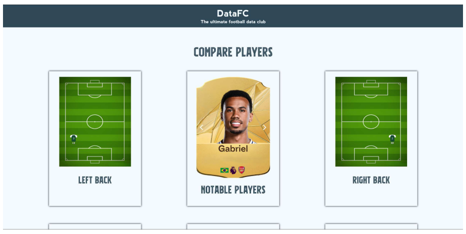
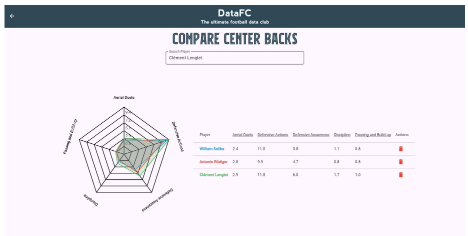


Figure 3: UI Home Page

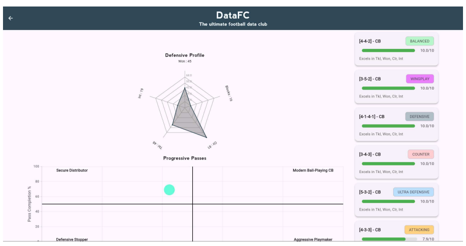
The initial interaction occurs at the **UI Home Page** (Figure 3). This serves as the central navigation hub, providing access to the core functionalities of the application, including player selection and league analysis. From this page, users can proceed to explore individual player statistics and comparisons, or explore their favourite leagues and teams.



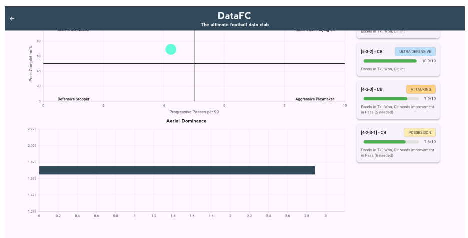
(a) Players section - Select player position



(b) Choose player to compare



(c) Player Visualization Example 1

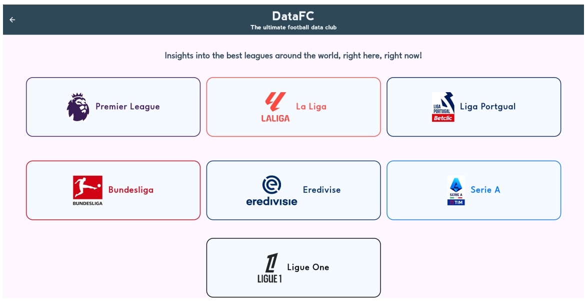


(d) Player Visualization Example 2

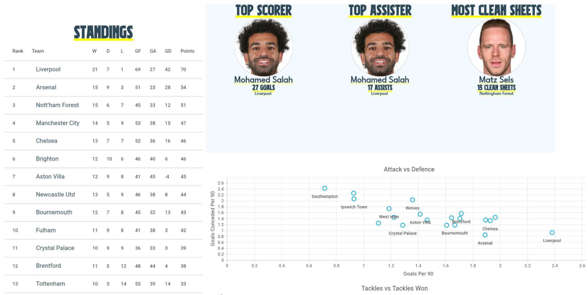
Figure 4: Player Selection and Visualization

The subsequent stage, depicted in Figure 4, involves **Player Selection and Visualization**. The workflow commences with the user selecting a specific player position, narrowing the scope of potential candidates (Figure 4a). Subsequently, the user can choose a particular player for comparative analysis (Figure 4b). The application then generates visualizations illustrating key performance indicators (KPIs) for the selected players, as shown in Figures 4c and 4d. These visualizations aim to provide a comprehensive overview of individual player performance.

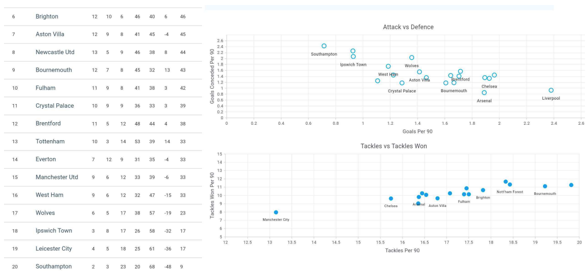
The final segment of the UI flow focuses on league-level analysis, as illustrated in Figure 5. This process begins with the user selecting a specific league of interest (Figure 5a). Following league selection, the application presents a series of dashboards providing an aggregate overview of league performance, as demonstrated in Figures 5b and 5c. These dashboards incorporate key metrics and visualizations to facilitate comprehensive league analysis.



(a) League Selection



(b) Premier League Dashboard 1



(c) Premier League Dashboard 2

Figure 5: League Selection and Dashboards

The overall design of the UI prioritizes ease of use and clarity of information presentation. The screenshot walkthrough presented in this section demonstrates a typical user journey and highlights the key functionalities of the application.

Chapter 6

Implementation

6.1 Data Pipeline

The data pipeline serves as the backbone of the system, ensuring that the data is systematically collected, cleaned and stored for efficient use for accurate analysis. The pipeline automates the extraction and preparation of data to be used in machine learning models.

6.2 Data Collection

The first step in the data pipeline is collection of data from external sources. The data is collected primarily from Fbref and Transfermarkt. Fbref provides data ranging from basic statistics for players like nationality, height, advanced on-field metrics such as expected goals and expected assists covering domestic leagues over forty countries. Transfermarkt gives detailed data about player transfers, including transfer fees, contract duration and clubs involved. Utilizing data from both the sources has offered a comprehensive perspective to the system. Multiple automated custom web scrapers were developed to systematically extract data related to players, teams, and the top five European domestic leagues. The scrapers are as follows:

1. **League Standings:** The system incorporates a web scraper tailored to retrieve the standings table of the top five domestic competitions in Europe allowing automated collection of team level data such as position, points, wins, losses and goal scoring statistics. Algorithm 1 shows the algorithm for the League Standings Scraper.

2. **Squad Stats Scraper:** The automated squad stats scraper ex- tracts team level data from Europe's top five leagues. The extracted data includes a vast set of tables which cover various performance dimensions such as standard stats (matches played, goals, xG), goalkeeping and advanced goalkeeping (save rates, post shot xG, etc.), shooting (shot volume, conversion), passing and pass types (progressive passes, pass lengths), goal and shot creation (SCAs, GCAs), defensive actions (tackles, interceptions), possession (carries, take-ons), playing time (minutes played, starts), and miscellaneous metrics (fouls, aerial duels, cards). This scraper enables the system to work with detailed and comprehensive statistical squad-level performance evaluation. Algorithm 2 shows the algorithm for the Squad Stats Scraper.

3. **Top Performers Scraper:** The Top Performers Scraper extracts data related to the top

performing players from Europe's top five leagues. The data includes information about the player with the most goals (number of goals, team name, player image link), the player with the most assists provided (number of assists provided, team name, player image link) and the goal keeper with the most clean sheets kept (number of clean sheets, team name, player image link). Algorithm 3 shows the algorithm for the Top Performers Scraper.

4. **Player Stats Scraper:** The Player Stats Scraper extracts player performance data. The data includes a wide range of performance metrics distributed in various categories. These include Standard Stats (appearances, minutes played, goals, and assists), Shooting (number of shots, shots accuracy, xG, xGoT), Passing (total passes, completion percentages, key passes), Pass Types (e.g. long passes, through balls, switches), Goal and Shot Creation metrics that capture both direct and indirect contributions to scoring opportunities, and Defensive Actions (tackles, interceptions, blocks). Possession-related (carries, touches, dribbles) as well as playing time (minutes per appearance, starting/substitution patterns) are also retrieved. This collection of scraper data allows the system to perform a detailed analysis of the contribution of a player throughout the season. Algorithm 4 shows the algorithm for the Player Stats Scraper.

5. **TransferMarkt Scraper:** Using the Transfermarkt scraper, the system is served with crucial off-field player metrics such as market value, injury status, and contract length, which are essential metrics consumed by the machine learning models for predicting the market prices of the players. Algorithm 5 shows the algorithm for the Transfermarkt Scraper.

6.3 Data preprocessing

Data preprocessing is an integral part of the methodology as it provides the system with clean and accurate data. The data preprocessing pipeline was implemented as a multistep approach to ensure the reliability and usability of the data. First, data from Fbref.com and Transfermarkt.com were consolidated based on the player's last name and age. In instances where the players' last names were the same, the positions of players were considered for correct aggregation. Secondly, several values were missing or zero by default (e.g., xG for most goalkeepers). To tackle such discrepancies, any row with more than eight-five percent missing values was dropped, ensuring robustness of the dataset. In the remaining dataset, numerical values were imputed using the median where the absence of values was insignificant. As the final step, the data on age and market values was put through the statistical technique called winsorization to limit the impact of outliers in the data. It was found that winsorization had an impact on the results and normalizing the data for players too old or too young aided in standardizing the data.

6.4 Feature Engineering

As part of the feature engineering process, the dataset was divided into ten classes: goalkeepers (GK), left backs (LB), right backs (RB), center backs (CB), center defensive midfielders (CDM), center midfielders (CM), center attacking midfielders (CAM), left wingers (LW), right wingers (RW), and center forwards (CF). For each class, customized metrics were developed using the preprocessed data. The metrics were as follows:

6.4.1 Goalkeepers (GK)

The following metrics quantify the on-field performances for goalkeepers.

6.4.1.1 Shots Saved

The shot-stopping ability of goalkeepers per 90 minutes was calculated using the formula:

$$\text{Shots Saved} = \frac{\text{Saves}}{90} \tag{6.1}$$

6.4.1.2 Expected Goals Prevention (EGP)

This custom metric quantifies the goals prevention performance of goalkeepers per 90 minutes played.

$$\text{Expected Goals Prevention (EGP)} = \frac{\text{PSxG} + \text{GA}}{90} \tag{6.2}$$

6.4.1.3 Cross and Aerial Control (CAC)

Shows how well the goalkeeper performs at catching or punching crosses coming into the 16-yard box per 90 minutes played.

$$\text{Cross and Aerial Control (CAC)} = \frac{\text{Stp}}{90} \tag{6.3}$$

6.4.1.4 Sweeper Keeper Activity (SKA)

Quantifies the goalkeeper's ability to perform sweeping actions outside the 16-yard box per 90 minutes played.

$$\text{Sweeper Keeper Activity (SKA)} = \frac{\text{OPA}}{90} \tag{6.4}$$

6.4.1.5 Distribution Ability

Shows how capable the goalkeeper is at distributing the ball with their feet. Calculated per 90 minutes played.

$$\text{Distribution Ability} = \frac{\text{Cmp} + \text{KP} + \text{FinalThird}}{90} \tag{6.5}$$

Table 1: Goal Keepers

Name	Shot Stopping	EGP	CAC	SKA	Distribution
Alisson	2.20	-0.01	0.33	1.87	26.26
G. Donnarumma	2.52	-0.03	0.43	0.55	25.21
J. Oblak	2.42	-0.08	0.61	0.81	20.73
M. Maignan	2.51	-0.17	0.74	1.89	35.85
T. Courtois	1.91	-0.06	0.43	0.57	29.52

6.4.2 Center Backs (CB)

The following metrics quantify the on-field performances for center backs. Table II displays a subset of the center backs dataset.

6.4.2.1 Defensive Actions

Custom metric showing the center back's defensive contribution on the field per 90 minutes played.

$$\text{Defensive Actions} = \text{Defensive Contribution} \tag{6.6}$$

Defensive Contribution =

6.4.2.2 Aerial Ability

Quantifies the aerial solidity of the center back per 90 minutes played.

$$\text{Aerial Ability} = \frac{\text{Won}}{90} \tag{6.7}$$

6.4.2.3 Passing Ability

Shows how well the center back passes the ball and progresses the ball upfield per 90 minutes played.

$$\text{Passing Ability} = \frac{\text{Cmp} + \text{KP} + \text{PrgP}}{90} \tag{6.8}$$

6.4.2.4 Positioning and Defensive Awareness

Quantifies the positional awareness of the center back on the field per 90 minutes played.

$$\text{Positioning and Defensive Awareness} = \frac{\text{Blocks} + \text{Clr}}{90} \tag{6.9}$$

6.4.2.5 Disciplinary Record

Shows how disciplined the center back is across the game. Calculated per 90 minutes played.

$$\text{Disciplinary Record} = \frac{\text{CrdY} + \text{CrdR} + 2\text{CrdY} + \text{Fouls}}{90} \tag{6.10}$$

Table 2: Center Backs

Name	Def. Actions	Aerial Duels	Passing	Def. Aware.	Discipline
Marquinhos	12.43	4.07	13.85	4.80	1.15
P. Cubarsí	8.11	2.72	11.35	3.37	0.70
P. Torres	8.02	2.32	9.25	3.60	0.40
V. van Dijk	11.55	2.45	8.02	5.68	0.51
W. Saliba	10.98	2.43	8.08	3.83	1.10

6.4.3 Full Backs (LB and RB)

The following custom metrics have been used to quantify the performances of left backs and right backs. Table III displays a subset of the fullbacks' dataset.

6.4.3.1 Defensive Duties

$$\text{Defensive Duties} = \frac{\text{Def 3rd} + \text{Int} + \text{Blocks} + \text{Clr} + \text{Recov}}{90} \tag{6.11}$$

6.4.3.2 Offensive Contributions

$$\text{Offensive Contributions} = \frac{\text{PrgC} + \text{PrgP} + \text{KP} + \text{xA}}{90} \tag{6.12}$$

6.4.3.3 Final Third Play

This custom metric shows how well the full-back makes themselves available to contribute in the final third, per 90 minutes played.

$$\text{Final Third Play} = \frac{\text{Crs} + \text{SCA} + \text{CPA} + \text{PPA}}{90} \tag{6.13}$$

6.4.3.4 Possession Play

Quantifies how well the full-back takes care of the ball on their feet, per 90 minutes played.

$$\text{Possession Play} = \frac{\text{Att 3rd possession} + \text{TotDist}}{90} \tag{6.14}$$

6.4.3.5 Dribbling Accuracy

Measures how well the player dribbles through the opposition's press.

$$\text{Dribbling Accuracy} = \frac{\text{Succ}}{90} \tag{6.15}$$

Table 3: Full Backs

Name	Att. Contributions	Final Third	Possession	Dribbling
A. Balde	9.24	8.29	29.83	0.43
A. Robertson	10.69	9.68	32.86	0.04
D. Udogie	9.48	3.56	26.86	0.11
F. Dimarco	7.41	14.59	35.74	0.03
F. Mendy	4.61	0.71	21.42	0.03

6.4.4 Central Defensive Midfielders (CDM)

The following custom metrics have been used to quantify the performances of center defensive midfielders.

6.4.4.1 Defensive Contributions

$$\text{Defensive Contributions} = \frac{\text{Tkl} + \text{Int} + \text{Blocks} + \text{Clr} + \text{Recov}}{90} \tag{6.16}$$

6.4.4.2 Passing Ability

$$\text{Passing Ability} = \frac{\text{Cmp}}{90} \tag{6.17}$$

6.4.4.3 Build-Up Play

$$\text{Build-Up Play} = \frac{\text{xA} + \text{xAG} + \text{Ast} + \text{PrgDist}}{90} \tag{6.18}$$

6.4.4.4 Ball Recovery & Defensive Work

$$\text{Ball Recovery \& Defensive Work} = \frac{\text{Recov} + \text{Int}}{90} \tag{6.19}$$

6.4.4.5 Line Breaking Passes

$$\text{Line Breaking Passes} = \frac{\text{KP} + \text{PrgP} + (1/3)\ \text{passing}}{90} \tag{6.20}$$

Table 4: Center Defensive Midfielders

Name	Def. Work	Passing	Build-Up	Recoveries	Line Breaking
B. Guimarães	10.26	3.07	22.80	5.98	13.75
Casemiro	17.54	6.53	24.28	6.80	11.14
G. Xhaka	9.33	3.71	37.14	5.57	23.84
J. Neves	13.41	5.73	26.61	7.46	16.13
Y. Bissouma	12.95	7.32	21.00	6.63	10.24

6.4.5 Central Midfielders (CM)

The following custom metrics have been used to quantify the performances of center midfielders.

6.4.5.1 Passing and Vision

Quantifies how well the center midfielders pass the ball to contribute to offensive phases of the play, per 90 minutes played.

$$\text{Passing and Vision} = \frac{\text{PrgP} + (1/3)\ \text{passing}}{90} \tag{6.21}$$

6.4.5.2 Dribbling

Shows how well the center midfielder takes care of the ball and dribbles past opponents, per 90 minutes played.

$$\text{Dribbling} = \frac{\text{Succ} + \text{PrgC} + \text{CPA}}{90} \tag{6.22}$$

6.4.5.3 Defensive Work

Explains the contribution of the center midfielder in defence, per 90 minutes played.

$$\text{Defensive Work} = \frac{\text{Tkl} + \text{Int} + \text{Blocks} + \text{Clr} + \text{Recov}}{90} \tag{6.23}$$

6.4.5.4 Chance Creation

Quantifies the creative qualities of the center midfielder.

$$\text{Chance Creation} = \frac{\text{SCA} + \text{xG} + \text{xA} + \text{xAG}}{90} \tag{6.24}$$

6.4.5.5 Possession Retention

Shows the ability of the center midfielder to retain the ball and not concede possession to the opposition, per 90 minutes played.

$$\text{Possession Retention} = \frac{\text{Cmp} + \text{KP} + (1/3)\ \text{passing} + \text{Succ}}{90} \tag{6.25}$$

Table 5: Center Midfielders

Name	Passing	Dribbling	Def. Work	Chance Creation	Possession
D. Rice	11.26	4.13	9.56	4.17	54.04
F. Valverde	13.30	2.67	10.72	2.91	67.67
Pedri	18.64	4.20	12.43	4.92	75.93
Vitinha	2.19	4.66	8.66	3.16	15.71

6.4.6 Central Attacking Midfielders (CAM):

The following custom metrics have been used to quantify the performances of central attacking midfielders.

a. Creativity and Playmaking: Quantifies the creativity of the central attacking midfielder, per 90 mintutes played.

$$\text{Playmaking} = \frac{xA + SCA + 1/3\_\text{passing}}{90s} \tag{6.26}$$

b. Ball Progression (BP): Numerifies the ability of the central attacking midfielder to move the ball up-field, per 90 minutes played.

$$\text{Ball Progression} = \frac{PrgP + PrgC}{90s} \tag{6.27}$$

c. Final Third Impact (FTI): Shows how much the central attacking midfielders impacts the game in the final (attacking) third, per 90 minutes played.

$$\text{Final Third Impact} = \frac{Att3rd\_possession + CPA + PPA}{90s} \tag{6.28}$$

d. Goal Threat: This metric shows the central attacking midfielder's ability to score goals, per 90 minutes played.

$$\text{Goal Threat} = \frac{xG + npxG + Gls}{90s} \tag{6.29}$$

e. Final Ball Efficiency (FBE): The ability of the central attacking midfielder to deliver the final ball, per 90 minutes played.

$$\text{Final Ball Efficiency} = \frac{xA + xAG + PPA}{90s} \tag{6.30}$$

Table 6: Central Attacking Midfielders

Name	Playmaking	BP	FTI	Goal Threat	FBE
D. Olmo	7.76	9.11	31.22	1.4	0.79
F. Wirtz	9.52	11.44	51.39	1.09	1.15
Isco	13.09	10.2	34.3	1.22	0.6
Ju. Bellingham	8.44	10.10	27.15	1.11	0.58
X. Simons	7.69	9.62	29.75	0.75	0.78

6.4.7 Wingers (LW and RW):

The following custom metrics have been used to quantify the performances of wingers.

a. Dribbling and Ball Carrying: Shows how well the winger is at dribbling the ball past opponents, per 90 minutes played.

$$\text{Dribbling} = \frac{Succ + PrgC + CPA}{90s} \tag{6.31}$$

b. Crossing and Playmaking (CAP): This metric quantifies the playmaking and crossing ability of the winger, per 90 minutes played.

$$\text{Crosses and Playmaking} = \frac{xA + xAG + Crs}{90s} \tag{6.32}$$

c. Goal Threat (GT): This metric shows the winger's ability to score goals, per 90 minutes played.

$$\text{Goal Threat} = \frac{xG + npxG + Gls}{90s} \tag{6.33}$$

d. Final Third Involvement (FTI): Shows how much the winger impacts the game in the final (attacking) third, per 90 minutes played.

$$\text{Final Third Impact} = \frac{Att\_3rd\_possession + CPA + PPA}{90s} \tag{6.34}$$

Table 7: Wingers

Name	Dribbling	CAP	Goal Threat	FTI
Bukayo Saka	10.07	7.82	0.89	42.62
Ousmane Dembélé	12.51	5.56	3.07	48.25
Rodrygo	9.39	4.02	0.72	41.80
Raphinha	6.39	7.80	1.73	38.85

6.4.8 Center Forwards (CF):

The following custom metrics have been used to quantify the performances of center forwards.

a. Goal Threat (GT): This metric shows the center forward's ability to score goals, per 90 minutes played.

$$\text{Goal Threat} = \frac{xG + npxG + Gls}{90s} \tag{6.35}$$

b. Chance Conversion : Quantifies how efficient is the center forward at converting chances, per 90 minutes played

$$\text{Chance Conversion} = \frac{G - PK + xG}{90s} \tag{6.36}$$

c. Link-up Play (LUP): Shows how well the center forward links up with the team through passing the ball, per 90 minutes played.

$$\text{Link-Up Play} = \frac{PrgR + xA + PPA}{90s} \tag{6.37}$$

d. Shooting Accuracy: Shows how accurately does the center forward shoot the ball on goal, per 90 minutes played.

$$\text{Shooting Accuracy} = \frac{SoT + Sh}{90s} \tag{6.38}$$

e. Penalty Box Presence (PBP): Quantifies the how present the center forward is in the penalty box, per 90 minutes played.

$$\text{Penalty Box Presence} = \frac{Att\_Pen}{90s} \tag{6.39}$$

Table 8: Center Forwards

Name	GT	Ch.Conv.	LUP	Shooting Accuracy	PBP
E. Haaland	2.18	0.05	4.12	2.06	6.20
H. Kane	2.36	0.07	7.05	1.73	6.07
K. Mbappé	2.02	0.05	14.00	2.25	9.70
L. Martínez	1.35	0.03	7.54	1.32	5.56
R. Lewandowski	2.76	0.08	5.66	1.65	5.96

6.5 Machine Learning Models

This section presents the proposed architecture of the machine learning model. The parameters and rationale behind the selected models are also explained.

6.5.1 Dimensionality Reduction

To avoid over-fitting, which is often introduced with high-dimensional data, PCA was performed after cleaning and feature engineering. This preprocessing reduced some dimensionality and highly correlated data, ensuring that the principal components identified by PCA were robust and effectively captured the variance.

- The Elbow Method (Scree Plot) explains the variance versus the number of components in a range (x, y).

To better understand the workings behind PCA, the mathematical formulas governing PCA are provided below.

Given a standardized dataset $\mathbf{X} \in \mathbb{R}^{n \times d}$, where n is the number of samples and d is the number of features, the covariance matrix is computed as:

$$\mathbf{C} = \frac{1}{n-1}\mathbf{X}^\top \mathbf{X} \tag{6.40}$$

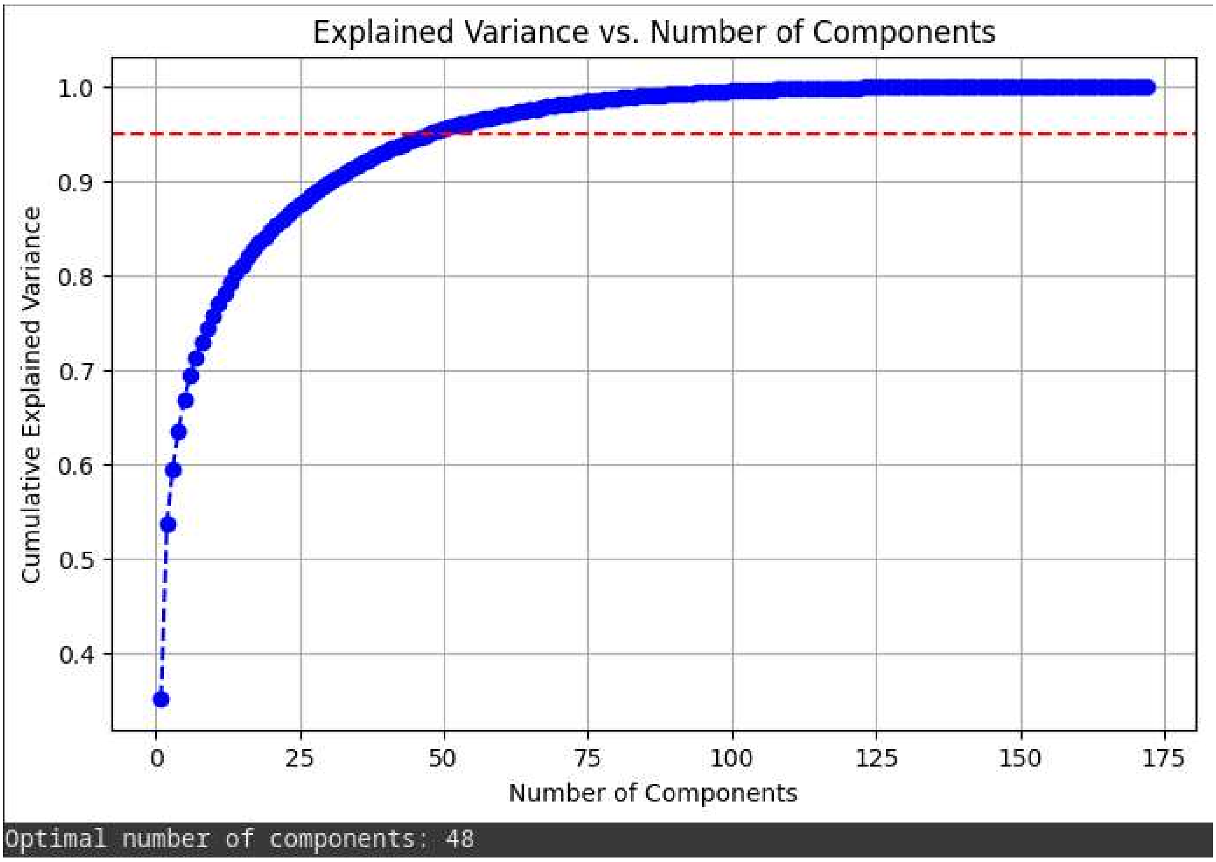


Figure 6: PCA Scree Plot

Eigenvalue decomposition is then performed on the covariance matrix:

$$\mathbf{C}\mathbf{v}_i = \lambda_i \mathbf{v}_i \tag{6.41}$$

where λ_i is the eigenvalue corresponding to the eigenvector $\mathbf{v}_i$. The eigenvectors are sorted in descending order of their eigenvalues.

Let $\mathbf{V}_k \in \mathbb{R}^{d\times k}$ be the matrix of the top k eigenvectors. The data is then projected onto the new k-dimensional subspace as[11]:

$$\mathbf{Z} = \mathbf{X}\mathbf{V}_k \tag{6.42}$$

Here, $\mathbf{Z} \in \mathbb{R}^{n\times k}$ is the transformed feature matrix in the reduced-dimensional space.

Following PCA, the transformed data are passed into an SEM, a stacked ensemble model, which performs the prediction of the market value of a player.

6.5.2 Stacked Ensemble Modeling

In recent times, multiple meta-heuristic learners and optimization algorithms have been doctored in the domain of football analytics[12]. This study presents a novel approach among those to predict the market value of a football player, based on real data, compared to the FIFA values used by many other studies.

Stacking is an ensemble approach that uses a 2-level approach, level-0 base learners and a level-1 meta learner. The level-1 meta learner is an aggregator that receives the output from single-based learners.

6.5.2.1 Base Learners

The base learners used are selected to capture linear and non-linear relationships in the data. Both parametric and non-parametric models were selected.

Linear Learners

- **Ridge Regression**: Also called Tikhonov regularization, it is used in ill-posed problems, useful to mitigate the problem of multicollinearity in regression problems, caused by a high dimensionality. It is useful in this study due to large number of principal components (>40). It employs L_2 regression to control multilinearity. Ridge regression minimizes the following loss function[13]:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda \|\beta\|_2^2 \right\} \tag{6.43}$$

- **Lasso Regression**: Lasso Regression is a statistical operator that penalizes the model to prevent overfitting and enhance accuracy. It does so by shrinking some coefficients to zero, effectively excluding them from the model. It employs L_1 regression for automation feature selection.

  Lasso regression introduces an L_1 penalty to promote sparsity[14]:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda \|\beta\|_1 \right\} \tag{6.44}$$

- **ElasticNet**: ElasticNet combines both, Lasso and Ridge regression, which improves its ability with regards with reconstruction. ElasticNet combines both L_1 and L_2 penalties[15]:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda_1 \|\beta\|_1 + \lambda_2 \|\beta\|_2^2 \right\} \tag{6.45}$$

Tree-Based Learners

- **Random Forest Regressor**: Random forest regression is a machine learning technique that uses multiple decision trees to predict continuous values using the bootstrap averaging method on the outputs given by each tree. It is included for its ability in smoothing out the errors from other learners, in the overall stacking architecture, while effectively capturing non-linear dependencies.

- **XGBoost**: By leveraging a magnitude of decision trees, it focuses on creating a powerful predictive model by using an iterative process that focuses on minimizing errors. XGBoost is proved to be unbeatable for handling structured data, along with its ability to address class imbalance, which was crucial in our study, due to the limited data of goalkeepers compared to other positions.

- **LightGBM**: LightGBM is designed specifically for large-scaled data, and employs a leaf-wise growth strategy, opposed to the level-based growth strategy used by other tree based algorithms. This allows it to have deeper trees and better predictive ability.

- **Gradient Boosting Regressor**: Similar to XGBoost, it builds the model iteratively.

- **AdaBoost Regressor**: AdaBoost is often used in conjunction with other machine learning algorithms to improve performance. The output of multiple weak learners is combined into a weighted sum that represents the final output of the model[16].

- **Support Vector Regression (SVR)**: SVR tries to find a function that is able to accurately predict the continuous output value for any given output value. It uses both linear and non linear kernels.

6.5.3 Meta Learner

The meta learner, also known as the Level-1 learner, is the final model that receives the output from all the base models, and predicts the market value by using the stacking ensemble algorithm. This study uses the Random Forest Regressor as the meta learner. A common strategy to train a stacking model is to use a hold-out set, where the dataset is split into two parts - the first layer is trained using the first part of the dataset, and the second layer is given the second set of data. The output from the meta model is used to create a new dataset, which makes this new dataset a 3D dataset. This new dataset ensures that the model learns the target value, given the inputs from the first layer. The rationale behind using the Random Forest in both base learners and as a meta learner is to use its ability to generalize well, and smoothen the results, and helps capture the complex relationships. As a base learner, it introduces diversity, and as a meta learner, its insensitivity to multicollinearity makes it a strong candidate to be used in both the layers.

The mathematical representation for the proposed model is given as:

$$\hat{y} = f_{\text{meta}}\left(f_1(\mathbf{Z}), f_2(\mathbf{Z}), \ldots, f_m(\mathbf{Z})\right) \tag{6.46}$$

Where:

- $\hat{y}$: Final prediction (market value)
- $f_1, f_2, \ldots, f_m$: Base learners (e.g., Ridge, Lasso, RF, XGBoost, etc.)
- $\mathbf{Z} \in \mathbb{R}^{n \times k}$: PCA-reduced feature matrix with n samples and k components
- f_{meta}: Meta learner (Random Forest Regressor)

Chapter 7

Testing

To evaluate the performance of the final SEM, multiple regression metrics were computed on both training and test sets. The rationale behind computing both training and testing sets was to check for overfitting. The difference between the training and test sets is a great metric to understand the state of the model. The higher the difference between these, the more the model overfits or underfits. The model achieved an R^2 score of 0.9464 on the training set and 0.9457 on the test set. The metrics are shown in Table 9.

The cross-validation R^2 score being close to the R^2 scores of the train and test sets indicates that the model generalizes well and avoids significant overfitting. Furthermore, the chosen combination of base learners and meta learner appears suitable for the type of data this study addresses.

Table 9: Evaluation metrics for the Stacking Ensemble Model

Metric	Train	Test
R^2 Score	0.9464	0.9457
Mean Squared Error (MSE)	9.73×10^{13}	9.69×10^{13}
Root Mean Squared Error (RMSE)	3,119,656.30	3,112,937.64
Mean Absolute Error (MAE)	2,199,469.47	2,259,460.70
Cross-Validation R^2 (Mean ± Std)		0.9383 ± 0.0029

Chapter 8

Results and Discussions

This section details the findings of our research, specifically the performance evaluation of the developed Stacked Ensemble Model (SEM) for predicting player market values in football. The analysis encompasses key performance indicators, a thorough examination of potential overfitting issues, and a discussion of the broader implications of the model's results within the football ecosystem.

8.1 Overall Performance

The SEM's efficacy was gauged using a variety of established metrics, assessed on both the training and test datasets:

- **R-squared (R^2):** The SEM yielded an R^2 of 0.9464 when applied to the training dataset and a closely comparable R^2 of 0.9457 on the test dataset. These results denote that the model effectively elucidates approximately 94.64% of the variance inherent in the training data and 94.57% of the variance observed in the test data.
- **Mean Squared Error (MSE):** The MSE registered at 9.73 x 10^{13} for the training set and 9.69 x 10^{13} for the test set. These values represent the average of the squared discrepancies between the model-projected and actual market valuations.
- **Root Mean Squared Error (RMSE):** Quantitatively, the RMSE was found to be 3,119,656.30 and 3,112,937.64 for the training and test sets, respectively. Measured in the same unit as the target variable (Euros), the magnitude of the model's average prediction error becomes more readily apparent. The value of 3,112,937.64 implies the model, on average, estimates market values within approximately 3.1 million Euros of the true value.
- **Mean Absolute Error (MAE):** An MAE of 2,199,469.47 was seen on the training and 2,259,460.70 on the test set. The MAE provides a robust indication of the magnitude of the average error, at roughly 2.26 million euros.
- **Cross-Validation R^2:** Cross-validation yielded a mean R^2 of 0.9383, with a standard deviation of ± 0.0029. This indicates the model's robust ability to generalize and the overall stability and reliability of the data utilized.

As can be seen in Table 6.1, these metrics suggest that the SEM exhibits strong predictive performance and generalization ability.

8.2 Overfitting Analysis

We explicitly explored the possibility of overfitting to ensure the reliability of our model's predictive capacity. As a gauge for overfitting potential, we compared the R^2 metric between our training and test sets. Here, a relatively small gap was observed (0.9464 and 0.9457, respectively) indicating the model's ability to generalize to unseen data.

The results from our cross-validation exercise (0.9383 ± 0.0029) corroborate this finding. A close alignment between the mean cross-validated R^2 and the R^2 calculated for the test set further suggest the model is not overly reliant on the nuances of the training data, demonstrating good out-of-sample performance.

8.3 Justification for Model Architecture and Component Choices

The SEM architecture was thoughtfully chosen to represent both linear and non-linear associations within the player market data. We chose the Random Forest Regressor as our meta-learner due to the following characteristics:

- **Generalization:** Random Forest's ability to generalize improves overall model robustness and accuracy.
- **High Volume Handling**: It effectively handles the large feature space while facilitating easier identification and prediction.

8.4 Limitations

Several limitations should be specified to guide the model's improvement in future iterations. These limitations include:

- Inherent biases and potential incompleteness in the data sourced from FBref and Transfermarkt, primarily due to their reliance on scouting subjective inputs.
- Exclusion of qualitative factors such as contract negotiations or player psychology data.

Future improvements include:

- Expanding the input data with additional sources that encompass player psychology and other factors such as contract negotiations.

- Additional consideration of complex machine learning algorithms for higher performance accuracy.
- Further investigation and analysis on feature importances for model improvement.

Chapter 9

Conclusion

By efficiently automating data extraction and processing of advanced player statistics from robust and vast data sources such as Fbref and Transfermarkt, the proposed system uses the extracted data to not only automate the manual and subjective process of scouting football players, but also drive the decision making process of coaches and managers. The system leverages complex machine learning models for predicting the market value predictions, along with clustering algorithms to identify players that are similar both, tactically and stylistically. The system includes role-specific metrics and performs position-aware analysis. Additionally, the usage of detailed visualizations such as radar charts and other performance graphs, makes the data analysis interpretable and actionable for coaches.

The system provides a robust framework to find replacements for football players, there are several aspects that exist for future enhancements. In the future, we would like to work on integrating match-by-match real time performance data which would offer dynamic tracking of players on the field. Additionally, building an all- inclusive analysis hub by including video analytics and sentiment analysis of players from media sources. Finally, expanding our databases to retired players, women's leagues and youth leagues would open underexplored doors.

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Publications

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We started this journey hoping to bring a positive impact, and the support and encouragement we received from everyone has been crucial in pursuing that aspiration.

Analysis Report

Scan details

Scan Time	Total Pages	Total Words
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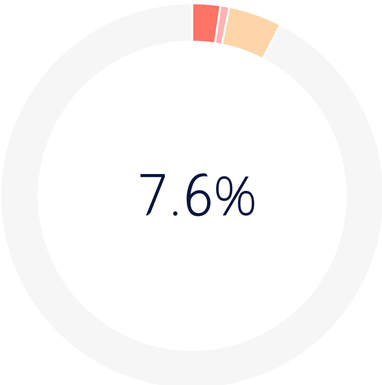
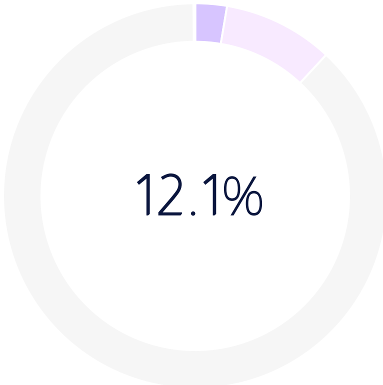


Plagiarism Types	Text Coverage	Words
Identical	2.4%	223
Minor Changes	0.7%	70
Paraphrased	4.5%	423
Excluded		
Omitted Words		2,694

AI Detection



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AI Text	12.1%	1,460
Low Frequency		321
Medium Frequency		10
High Frequency		8
Human Text	87.9%	7,967
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Comparative Analysis of Data Driven Techniques to Predict Transfer Prices of Football Players

Shubh Harde
Artificial Intelligence and Data Science
Dwarkadas Jivanlal Sanghvi College
Of Engineering
Mumbai, India
shubhharde158@gmail.com

Vedant Bhawnani
Artificial Intelligence and Data Science
Dwarkadas Jivanlal Sanghvi College
Of Engineering
Mumbai, India
bhawnanivedant@gmail.com

Shruti Dodani
Artificial Intelligence and Data Science
Dwarkadas Jivanlal Sanghvi College
of Engineering
Mumbai, India
shruti.savant@djsce.ac.in

***Abstract*— Football clubs from all around the world are in constant business of buying and selling players each transfer window. These transactions of signing and selling players involve multi-million dollar deals. Therefore, it is essential for buyer clubs to estimate the cost of acquiring the services of a player they have set their eyes upon before they make the decision of spending millions of dollars for that particular player. This need has caught the attention of researchers, statisticians and enthusiasts of the sport, which has led to the development of several techniques and platforms which predict the how much the player would cost. Transfermarkt is one such platform which relies heavily on its community to decide market values of players. This assessment is subjective and results in inconsistencies. As a result, there is a proliferation in the number of data-driven techniques being developed to statistically predict price of players. In this paper, we review and compare such several data-driven techniques for predicting player prices in the footballing world.**

Keywords—Football ,player valuation, transactions, buyer clubs

I. Introduction

Football is known as the world's sport as it is the most popular sport in the world [1]. There are more than 200 professional football leagues all around the globe [2]. Among these leagues, some renowned leagues are England's Premier League, Spain's EA Sports La Liga, Italy's Serie A, Germany's Bundesliga and France's top flight, Ligue 1. All these leagues have 15-20 teams competing for the title each season. Put together, thousands of players play in the football leagues all over the world, each year. Players move around from team to team on a regular basis. When a player wants to make a move from one team to another, the two major parties involved are, the engaging team and the releasing team who often work to reach an agreement through an intermediary known as the player agent.

For any player, there are two types of fees, which are often used interchangeably, the transfer value and the market value. In reality, these are two distinct values. The market value is defined as the financial value of the player based on performances. The transfer value is defined as how much the player would cost the buying team. Transfer fees are heavily influenced by factors such as the player's image, the player's relationship with their current team, the shirt selling and fan pulling power of the player along with the length of the current contract and age of the player. In some cases, the transfer fees also include agent fees. The standing transfer fee record is €222 million paid by Paris Saint Germain to F.C. Barcelona for acquiring the services of Neymar Jr. in 2017.

Not over paying for any player is always a priority for a club trying to sign new players to strengthen the team. Over paying for an underperforming player could cause catastrophic harm to the club both, financially and sportingly. Hence, it is important for decision makers at a club to predict and evaluate the market value and transfer value of players.

This paper exhibits a thorough analysis of past work done for predicting the market value and transfer prices of football players. We first review the existing literature on the topic of transfer and market fees, describe all the data sources put to use and machine learning techniques used in the literature. Followed by putting forth the areas of improvement in the literature that we think can be worked upon by other researchers.

II. Literature Review

The prediction of football players' market value has been studied widely, with researchers employing different methods, datasets and algorithms to enhance prediction accuracy. This section encapsulates a comprehensive literature review focused on the review of literature delving into the prediction of market value of players through machine learning and deep learning algorithms. Some researchers have found out some parameters which play an important factor in predicting the market value of a player. Age is included as one of the important factors, with young players demanding more value due to their potential for growth. Similarly, players with high popularity tend to bring their fans with them, leading to an increase in their market value.[6] The position of a player is also thought to play an important role, with attackers usually getting more importance.[5]

Beginning with Carmichael & Thomas (1993), economists have used regression models to identify the determinants of transfer fees [3]. Since then several researchers have followed a similar trend. Mustafa A. Al-Asadi et al.[6] used data from FIFA as true values and used different linear and non-linear models to predict the market price of a player. They employed 9 parameters, such as international reputation, weak foot column, etc.

Stanojevic and Gyarmati[4] presented their research on statistical measures, and obtained data from sports analyst company InStat, and transfermarkt (TM). The research aimed to estimate the market value of 12,858 players based on player performance metrics. The models were built on 45 predictors, and their results outperformed widely used transfermarkt.com market value estimates.

Muller et al.[7] presented a data-driven approach to overcome the limitations of crowd-sourcing. The researchers used the data from top 5 European leagues. They created a dataset using the attributes such as player characteristics - age, position, nationality. Muller et al.[7] took a unique approach by including data from Wikipedia, Facebook and Google metrics at that time. They employed a linear regression model, and results achieved were within the scope of crowdsourced estimates.

Dobson et al.[8] explored the effects of player metrics on transfer fees and discovered that transfer fees are volatile across segments even in a single competition. More recently, Depken II & Globan[9] use linear regression to identify that English clubs pay a premium in the transfer market, compared to clubs from other European countries.

Yigit et al.[10] presented an innovative approach to assessing the player values. They leveraged a wide range of player attributes, including on-field performance metrics, demographic data, and market factors, to predict player market values. The dataset comprised football players from major leagues. 5316 players from 11 major leagues across Europe and South America were considered. Data from the football manager simulation game was collected and merged with the transfer value from Transfermarkt. The most resultant values were in accordance with the current market values [12].

Behravan et al [11] took a distinctive approach to predict the market values of a player, by employing Particle Swarm Optimization. The data collected was from the FIFA 20 dataset, and the value of a player in the dataset was considered the true value. The players were divided into 4 clusters based on positions using an automatic clustering algorithm. According to the authors, the RMSE and MAE for their method are 2,819,286 and 711,029,413, respectively, while the results by Muller [7] were 5,793,474 and 3,241,733. These results indicate that their methods had a significant advantage over other methods [10]

Ian et. al[3] investigated the use of machine learning to estimate transfer fees, utilizing data from sofifa.com and transfermarkt.com. They trained both linear regression and XGBoost models on a range of performance metrics, including those from Instat and GIM performance ratings. Their findings indicated that the XGBoost model outperformed the linear regression model in predicting transfer fees. This research highlights the potential of machine learning to inform transfer decisions, addressing the question of "what is the expected fee of a player given their past performance?" The authors suggest further work to assess the "reasonableness" of transfer fees based on post-transfer performance, potentially leveraging the same data sources and machine learning techniques.

III. Data Sources

The quality of data plays a significant role in determining the real life performance of the algorithms. The model learns the existing data and outputs new responses, based on patterns found in the fed data. Hence, the data used needs to be not only accurate but also diverse. It needs to take into account a variety of possible factors that may be helpful in determining the output. In this section, we will discuss the different datasets/data sources used over the years to predict the transfer prices or the market price of a football player.

Several papers make use of performance metrics and event data collected from professional leagues, which was collected by scraping web pages. Other papers follow a more statistical approach for their analysis. Behravan and Razavi[11] looked to address the drawbacks of transfermarkt market value by using data from FIFA 20, by EA Sports. A few other authors followed a similar approach by using FIFA game data, such as Mustafa et al[6]., Vinscent Stevel et al., V. B. Jishnu et al.[12] Each of these authors use data from FIFA game, and consider those values to be the real values. Furthermore, some authors also specify the reason for using this dataset being a lack of real world statistical data for niche players.

A lot of research done in this field relies heavily on the transfer data from TransferMarkt(TM), and statistical data from fbref.com. TransferMarkt has been widely used due to the crowd-sourced player valurations. Members of the website offer their valuations of players and a panel of experts calculates a weighted average of the values to arrive at a single transfer value for each paper. The panel of experts calculate the weights based on judging how accurately each member has valued players historically. fbref.com provides a comprehensive study of football players, from basic information such as age, height and nationality, to more statistical information such as xG.

Another online source used for data analysis is sofifo.com. Player ratings have most commonly been taken from sofifo.com website. Members of the website provide ratings of players in many attributes(passing, shooting etc.), with editors reviewing these before presenting single values for each player. Yigit, Samak & Kayak[10], and Behravan & Razavi[11], both use crowd-sourced sofifa player ratings.

Other data sources include InStat, used by McHale & Holmes[3].

A study by Stanojevic and Gyarmati[4] relied on player tracking data and match event data, gathered from various leagues, to assess the technical aspects of players' performances. This data-driven approach allowed the researchers to estimate player values more accurately by focusing on specific in-game actions.

Other papers, such as that by Dobson and Gerrard[8], use historical transfer fee data from English soccer, which provides a comprehensive view of how player values have evolved over time in one of the sport’s most commercially significant leagues.

Apart from the data sources, another interesting aspect is the diversity of data used. While Depken II & Globan[9] use data from Europe’s top five leagues. Qing et al.[5] uses the UEFA championship performance data. Stanojevic and Gyarmati[4] also relied on player tracking and match event data, which provided a new way of thinking about the data that can be used. McHale & Holmes[3] use data from nine seasons starting with the 2011/12 season, till the 2019/20 season.

By leveraging the data obtained from these sources, ranging from professional metrics to crowd opinions to game statistics, they provide a holistic view of predicting transfer fees of a player. The growing amount of data makes it easy to envision the similar projects will be able to use the data for innovative and elegant purposes like transfer value prediction and other analysis.[11]

IV. Algorithms Used

Linear Regression: Linear Regression assumes a linear relationship between the input variables and the output variable (the target). McHale & Holmes[3] have used it to model the relationship between on-field performance metrics and their transfer fees Where y is the transfer fee, x1, x2,….,xn are the independent variables and E is the error term. In McHale & Holmes[3] Linear Regression provides a baseline model to learn how individual features of players (like age and goals per game) are related to transfer fees. However this technique struggles to capture complex non-linear relationships. Al Asadi and Sakir Tasdemir[6] also use Linear Regression to provide a rudimentary modelling of the relationship between players' attributes and market values. Only the players' potential is used as an independent variable in their study for this model. Linear Regression achieves a low accuracy with RMSE of 5.46 and R-Squared of 0.43.

Elastic Net Generation: The ENG regression mixes Lasso and Ridge regressions to handle the multicollinearity efficiently and perform variable selection. Elastic Net Generation is used in McHale & Holmes [3] for selecting only the most important features and managing overfitting. This is useful when there are many correlated variables.

XGBoost (Extreme Gradient Boosting): XGBoost is an ensemble learning technique which builds a series of decision trees, where each tree is aimed at correcting the errors of the previous one. In this technique, each tree learns from the mistakes of the previous trees, reducing the residual errors step by step. L1 and L2 regularisation both are used to prevent overfitting. XGBoost identifies the most important features that impact the target variable which makes the model more interpretable. McHale & Holmes [3] use XGBoost because it is very capable at capturing complex, non-linear relationships between player performance and transfer fees. XGBoost achieves the best performance compared to other methods. Yigit Samak and Kaya[10] also used XGBoost to improve prediction accuracy by adding trees that correct errors of previous trees, while controlling for overfitting. XGBoost achieved the lowest MSE of 0.170, making it the best performing model in the study. Jishnu et al.[12] used XGBoost to predict transfer values of players using the FIFA 22 video game dataset and other advanced player performance metrics. The model performed well across all categories of players with an R-Squared value of 0.805, 0.805, 0.81 and 0.856 for goalkeepers, defenders, midfielders and attackers respectively.

XGBDART (Dropout Additive Regression Trees): XGBDART extends XGBoost by adding a "dropout" technique which is inspired by neural networks, to randomly drop trees during the training phase. This prevents certain trees from dominating the model, resulting in better generalisation and less overfitting. McHale & Holmes [3] apply XGBDART as a way to regularise the boosted trees, improving generalization on unseen data.

Mixed Effects Linear Model: Mixed Effects Linear Model is useful when the data is hierarchical or grouped data because it allows for random effects to learn group-level variability. In McHale & Holmes[3] clubs are considered to be groups and the influence of transfer fees is treated as random effects. The authors use this model to model the varying financial behaviour of both, the buying and selling clubs while estimating transfer fees of the players. By doing this, the variability in the club's strategies is better captured.

Random Forests: Random forests construct multiple decision trees during the training phase and output the mean prediction for regression tasks. Here, each decision tree is trained on a random subset of data, which helps in reducing overfitting. The final prediction is an average of all trees' output. Stanojevic and Gyarmarti[4] use performance metrics like goals, assists, tackles and passes to predict players' market values. Accuracy and performance of random forests in predicting values is compared to other algorithms in the paper. Al Asadi and Sakir Tasdemir[6] have also incorporated random forests in their study to obtain a final prediction of players' market values. Random Forests perform better than the other algorithms in the study with an RMSE of 1,64 and R-Squared of 0.95. Random Forests were also used by Jishnu[12] et al. and had an R-Squared 0.783 for goalkeepers, 0.78 for defenders, 0.751 for midfielders and 0.783 for attackers. However, in Jishnu et al[12]. Random Forests fall short of other algorithms used.

Gradient Boosting Trees: GBT builds models in a sequence by minimising the residual errors of previous models. GBT is a more powerful and flexible model compared to Random Forest as it corrects the mistakes of the previous trees. GBT is particularly useful when dealing with complex and non-linear relationships of the data. Stanojevic and Gyarmarti[4] use GBT to predict market values of players taking into account a wide array of player statistics and correcting them, for inconsistencies. GBT is used as the main model for predicting the market value, which is attested against the actual values from Transfermarkt. In Jishnu et al,[12] GBT performed the best in the attackers category by achieving a R-Squared of 0.86, and had a strong performance in other categories as well with R-squared values of 0.813 for goalkeepers and 0.788 for defenders.

Coefficient of Variation (CV): The CV is the ratio of the standard deviation to the mean of a player's performance metrics. This provides a normalized measure of variability which allows comparisons across different players and performance metrics. In Yi, Qing et al.[5] CV is applied on player statistics to evaluate match-to-match performances for players across multiple positions and contexts. Higher the CV, more the variability in performance, while lower variability suggests more consistent performance.

Magnitude Based Inference: MBI is a statistical approach that is used to estimate the possibility of observed features being significant according to predefined thresholds. In Yi, Qing et al.[5] MBI is used the measure the difference between players' performance spanned over several situational contexts.

Effect Size with Confidence Intervals: Effect Size is computed to understand the magnitude of difference in players' in match performances across multiple categories. Effect Sizes calculate the amount of difference, independent of sample size. In Yi, Qing et al.[5] the effect sizes are calculated to compare the variability of player performance metrics over several different situations, such as home vs. away games.

Multiple Linear Regression: Multiple Linear Regression is also used by Al Asadi and Sakir Tasdemir[6] to model more relationships between the market values and player attributes. Several independent variables are used such as age, height, potential, international reputation, weak foot, team position, shooting, passing and dribbling. MLR shows an improvement over linear regression with an RMSE of 4.66 and R-Squared of 0.56. MLR is also used by Yigit Samak and Kaya[10] to predict market value of players. They use it as a baseline model which produced a mean squared error of 0.768 when validated using cross-validation.

Decision Trees: Al Asadi and Sakir Tasdemir[6] used to recursively split the data into small subsets of player attributes. To minimise the error in predicting the market values of the players, the tree keeps branching based on the most significant features which helps in handling non-linearity. Decision trees significantly improved upon the performance of linear and multiple linear regression by achieving a RMSE of 2.71 and R-Squared of 0.87.

Multilevel Regression Analysis: Muller Simons and Weinmann[7] employed this algorithm to make an estimation of market values of football players by considering multiple features including player characteristics, performance metrics, and popularity data. This model was selected by the authors because the data is hierarchical (players nested in teams and teams nested in leagues) as well as longitudinal (spanned across multiple seasons). This model achieved a +3.4% relative difference of RMSE between crowd estimates and model estimates and a +3.6% difference of MAE between crowd estimates and model estimates

Ridge Regression: Used in Yigit Samak and Kaya[10], Ridge regression is an improvement upon linear regression which regularises the coefficients of less significant features, thus preventing overfitting. The goal of ridge regression is to shrink the coefficients of the insignificant variables towards zero while still keeping the coefficients of the significant features intact. The MSE of the ridge regression model was 0.608.

Lasso Regression: Yigit Samak and Kaya[10] also use Lasso regression goes one step further than ridge regression and sets the coefficients of insignificant features to exactly zero. The MSE of Lasso regression was 0.590

APSO-Clustering: APSO-Clustering is an automatic clustering method which consists of two steps. The first step involves breaking down large and complex datasets into optimal clusters and the second step identifies the correct positions of the clusters obtained at the end of the first step. Iman Behravan and Mohammad Razavi[11] used APSO-Clustering's first phase to cluster players based on their positions. This helped ensure that the models applied later are specific and relevant to each position.

PSO-SVR: PSO-SVR is a hybrid machine learning model which is made by combining Particle Swarm Optimization and Support Vector Regression. In this hybrid model, PSO performs two tasks, feature detection and parameter tuning of SVR. PSO iterated through the search space to identify the most significant subset of features and optimises SVR's kernel parameters. In Iman Behravan and Mohammad Razavi's [11] PSO-SVR was applied to each cluster to estimate the market values of players. PSO-SVR achieved a accuracy of 74%, which outperformed other algorithms like GWO (Grey Wolf Optimizer) (70% accuracy), IPO (Inclined Planes System Optimization) (67% accuracy) and WOA (Whale Optimization Algorithm) (64% accuracy).

V. Conclusion and Future Work

In this paper, we have provided an in-depth study and analysis of the existing literature from the year 1993 to 2023 of predicting football players' market and transfer values. Our review compasses of 10 research papers which made use of 15 different machine learning techniques to estimate the market and transfer values. Out of all the models used in the vast literature, XGBoost has proven to be the best performing model across multiple papers as it achieved a low MSE of 0.170 in Yigit Samak and Kaya [10], and an R-Squared of 0.805 in Jishnu et al [12]. On the other end of the spectrum, linear regression came out to be the worst-performing model in the referred works. Linear regression was often used as a baseline model in the literature because it fails to capture non-linear relationships in the datasets.

In future research, we plan to develop a comprehensive Transfer Value Index (TVI) which will serve as a single metric required to estimate the transfer value of football players. This index will cover various dimensions that are involved in deciding the transfer values of players. The index will combine advanced in-match statistics – such as xG, PsXG, xGA, passing accuracy, and tackling accuracy – with off-field factors that have a significant influence on transfer fees. The player's reputation with both the fans and the club, including media presence and fan pulling power will also be used to reflect the player's brand value. Finally, we will also take into account the economic as well as the sporting position of buying and selling clubs. Therefore, by combining these variables into a single index we aim to offer a holistic, data-driven and accurate estimation of player transfer fees which would serve as a valuable tool for clubs, agents and fans in future player transfers.

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Stacked Ensemble-Based Framework for Predicting Market Value and Tactical Fit in Football Transfers

Shubh Harde
Artificial Intelligence and Data Science
shubhharde158@gmail.com

Vedant Bhawnani
Artificial Intelligence and Data Science
vedantbhawnani@gmail.com

Shruti Savant
Professor, Artificial Intelligence and Data Science
shrutisavant@gmail.com

Abstract*—The transfer markets in football are a dynamic and pivotal period which entails a state of volatility where teams and clubs strategize and aim to strengthen their teams. This is more often than not, preceded by in-depth analysis of data related to hundreds of promising and prospective players to find the perfect replacement for the outgoing player. This analysis currently includes labour intensive tasks of manual video reviews and scouts going to games to watch a prospect play. This paper introduces the Football Player Replacement Finder, a novel approach to reduce the complexity and time required for scouting and acquiring impactful talents by using advanced machine learning models and automated data scraping pipelines. Our system employs supervised models for gauging the performance and price of football players along with clustering techniques for player profiling, enabling stat-by-stat comparison of players. By integrating advanced metrics along with appealing visualisations, our system empowers decision-makers to streamline their scouting process and uncover valuable talents effectively.

Index Terms—**Football analytics, Player replacement, Machine learning in sports, Player performance prediction, Transfer market strategy, Clustering for player profiling, Football scouting automation**

I. Introduction

The transfer window months of January and July each year are one of the most critical time periods for any football club looking to strengthen their squad. In this period, the clubs focus heavily on identifying potential signings, while keeping a close eye on the departing players. Each club has to identify suitable replacements while ensuring that they do not overpay for a player as adhering to the budget is a key requirement for any club. Scouting players and ensuring that the scouted players are within the budget, is a monumental task that requires a deep analysis of a wide range of factors, such as player statistics, market conditions such as inflation and volatility, the team effect on team dynamic of incorporating a new player, and any ego clashes that may arise in the dressing room among players. Traditionally, this process includes extremely laborious scouting methods, involving going through extensive video footage, gathering subjective reports and insights, and manually comparing hard statistics of players. These methods have always been time consuming and with the exponential increase in the amount of data and advanced metrics, it is only getting increasingly difficult to keep up with the demands of modern football. The recent advancements in football analytics have introduced multiple data-approaches to player evaluation. Platforms such as FBref [1] and Sofifa [2] offer vast amounts of data and player statistics and attributes, which have become an important tool for the recruiters. Despite the availability of these insights, the process of finding replacements remains labour-intensive. Traditional methods of scouting do not generally incorporate data driven approaches while handling larger and more complex datasets in the modern era of players scouting. This paper proposes an advanced system of player recruitment and replacement process by automating data collection, analysis and comparison. The proposed system uses machine learning models, including supervised learning and clustering algorithms to predict player performance and identify statistically similar players. By making use of similarity metrics such as Euclidean distance, cosine similarity or the Pearson Correlation, the system enhances the accuracy of player comparisons, ensuring a more relatable match between the outgoing player and the potential replacement of the outgoing player, The integration of automated data scraping pipelines allows for faster and more effective comparison of players based on on-field metrics such as expected goals, expected assists, goals, assists, passing accuracy, progressive carries and other related statistics. These metrics, combined with similarity measures, create a comprehensive view of player performance, enabling deeper and more accurate analysis, ensuring that the players are suitable not only for the immediate requirements of the club, but also with the tactical approach of the manager and the coaching staff along with the long-term goals of the club. By reducing the reliance on manual processes, risks like human errors, and biases are eliminate that are brought into the system by scouts or managers' prejudices. Player Replacement Finder aims to enable clubs in easier and faster identification of potential players with greater accuracy. The proposed system not only enhances the precision of player comparisons models, but also offers intuitive visualisation approaches that helps clubs take faster decisions in choosing the right candidate and saving them from over spending unnecessarily. This approach has the potential to optimise transfer strategies, which indirectly also affects the team performance. The remainder of this paper is organised as follows: Section 2 reviews the current literature on football player replacement and data analytics already accomplished in this domain. Section 3 outlines the methodology used to develop the Player Replacement Finder system, including the data sources and machine learning models employed. Section 4 presents the results and validations of the system, and section 5 concludes with discussion of the system's impact on modern football transfers and potential future development.

II. Literature Review

The prediction of football players' market value has been studied widely, with researchers employing different methods, datasets and algorithms to enhance prediction accuracy. This section encapsulates a comprehensive literature review focused on predicting the market value of players through machine learning and deep learning algorithms. Few researchers have found out some parameters which play an important factor in predicting the market value of a player. Age is included as one of the important factors, with young players demanding more value due to their potential for growth. Similarly, players with high popularity tend to bring their fans with them, leading to an increase in their market value [3]. The position a player plays is also thought to be important, with attackers usually having higher market values [4]. Beginning with Carmichael & Thomas (1993), economists have used regression models to identify the determinants of transfer fees [5]. Since then several researchers have followed a similar trend, with many researchers following regression-based models to forecast the player transfer fees. Mustafa A and Al-Asadi used data from FIFA as true values and used different linear and non-linear models to predict the market price of a player [6].

They employed 9 parameters, such as international reputation, weak foot column, etc. Stanojevic and Gyarmati presented their research on statistical measures, and obtained data from sports analyst company InStat, and Transfermarkt [7]. The research, following a more traditional approach, aimed to estimate the market value of 12,858 players based on player performance metrics. Clustering techniques were deployed to analyze player performance data, and the model was built on 45 predictors, with their results outperforming widely used transfermarkt.com market value estimates, paving way for more precise predictions with the help of data analytics and finer data [8]. Muller et al. [3] presented a data-driven approach to overcome the limitations of crowd-sourcing. The researchers used the data from top 5 European leagues. They created a dataset using the attributes such as player characteristics - age,position, nationality. Muller et al. took a unique approach by including data from Wikipedia, Facebook and Google metrics at that time. They employed a linear regression model, and results achieved were within the scope of crowdsourced estimates . Dobson et al. [9] explored the effects of player metrics on transfer fees and discovered that transfer fees are volatile across segments even in a single competition. More recently, Depken II & Globan use linear regression to identify that English clubs pay a premium in the transfer market, compared to clubs from other European countries.[10] Yigit et al. presented an innovative approach to assessing the player values. They leveraged a wide range of player attributes, including on-field performance metrics, demographic data, and market factors, to predict player market values. The dataset comprised football players from major leagues. 5316 players from 11 major leagues across Europe and South America were considered. Data from the football manager simulation game was collected and merged with the transfer value from Transfermarkt. The most resultant values were in accordance with the current market values. [11] Behravan et al. took a distinctive approach to predict the market values of a player, by employing Particle Swarm Optimization. The data collected was from the FIFA 20 dataset, and the value of a player in the dataset was considered the true value. The players were divided into 4 clusters based on positions using an automatic clustering algorithm. According to the authors, the RMSE and MAE for their method are 2,819,286 and 711,029,413, respectively, while the results by Muller[6] were 5,793,474 and 3,241,733. These results indicate that their methods had a significant advantage over other methods.[12] Ian et. al [13] investigated the use of machine learning to estimate transfer fees, utilizing data from sofifa.com and transfermarkt.com. They trained both linear regression and XGBoost models on a range of performance metrics, including those from Instat and GIM performance ratings. Their findings indicated that the XGBoost model outperformed the linear regression model in predicting transfer fees. This research highlights the potential of machine learning to inform transfer decisions, addressing the question of ”what is the expected fee of a player given their past performance?” The authors suggest further work to assess the ”reasonableness” of transfer fees based on post-transfer performance, potentially leveraging the same data sources and machine learning techniques.

III. Methodology

The proposed system uses advanced on-field player performance metrics, domestic and continental performance of football clubs, players’ perceived market value, player injury data and domestic competition metrics like standings and top performers. The data is collected from FBref and Transfermarkt using automated web scraping scripts. The collected data is put through a data processing pipeline which cleans and transforms the data to match the needs of the system. The preprocessed data is used by machine learning models for calculating consolidated metrics for comparing players and teams, determining similar players, formation fit analysis and market price prediction. Figure 1 shows the proposed methodology.

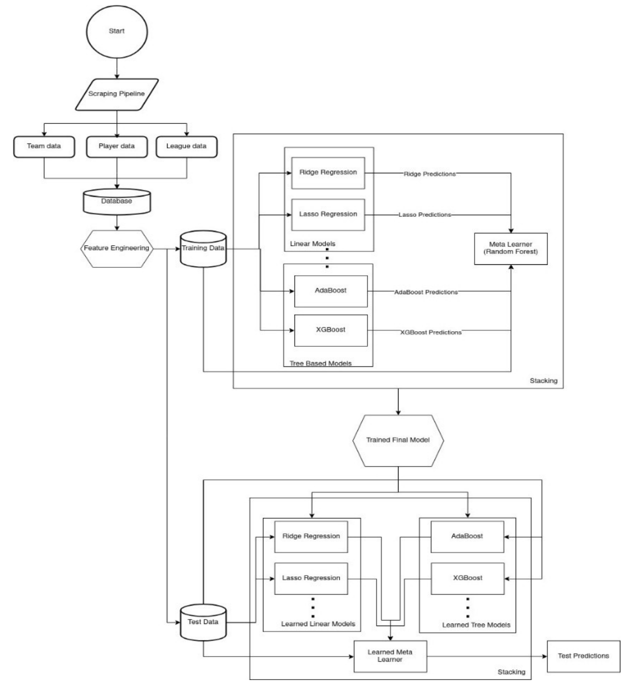

Fig. 1. *Proposed Methodology*

A. Data Pipeline

The data pipeline serves as the backbone of the system, ensuring that the data is systematically collected, cleaned and stored for efficient use for accurate analysis. The pipeline automates the extraction and preparation of data to be used in machine learning models.

B. Data Collection

The first step in the data pxipeline is collection of data from external sources. The data is collected primarily from Fbref and Transfermarkt. Fbref provides data ranging from basic statistics for players like nationality, height, to advanced on-field metrics such as expected goals and expected assists covering domestic leagues over forty countries. Transfermarkt gives detailed data about player transfers, including transfer fees, contract duration and clubs involved. Utilizing data from both the sources has offered a comprehensive perspective to the system. Multiple automated custom web scrapers were developed to systematically extract data related to players, teams, and the top five European domestic leagues. The scrapers are as follows:

1) League Standings: The system incorporates a web scraper tailored to retrieve the standings table of the top five domestic competitions in Europe allowing automated collection of team level data such as position, points, wins, losses and goal scoring statistics. Algorithm 1 shows the algorithm for the League Standings Scraper.

2) Squad Stats Scraper: The automated squad stats scraper extracts team level data from Europe’s top five leagues. The extracted data includes a vast set of tables which cover various performance dimensions such as standard stats (matches played, goals, xG), goalkeeping and advanced goalkeeping (save rates, post shot xG, etc.), shooting (shot volume, conversion), passing and pass types (progressive passes, pass lengths), goal and shot creation (SCAs, GCAs), defensive actions (tackles, interceptions), possession (carries, take-ons), playing time (minutes played, starts), and miscellaneous metrics (fouls, aerial duels, cards). This scraper enables the system to work with detailed and comprehensive statistical squad-level

Algorithm 1 League Standings Scraper

```
procedure PATHDECIDER(league)
    folder_path ← "assets
Data
textbackslash" + league
    if folder_path exists then
        return folder_path
    else
        Create directory at folder_path
        return folder_path
    end if
end procedure
procedure LEAGUESTANDINGSCSV(league)
    link ← lookup league in league_links
    df ← read HTML tables from link
    Drop columns "Notes" and "Attendance" from df[0]
    folder_path ← PATHDECIDER(league)
    csv_path ← join folder_path and "league_Standings.csv"
    Save df[0] as CSV to csv_path without index
end procedure
```

Algorithm 2 Squad Stats Scraper

```
Input: URL of a team page from FBref
Output: Dictionary of DataFrames for multiple squad stats categories
procedure TEAMSCRAPER(url)
    Set self.url to given url
end procedure
procedure GET_DFS
    Call get_all_team_stats_from_URL(self.url)
    return Dictionary of DataFrames
end procedure
procedure GET_ALL_TEAM_STATS_FROM_URL(url)
    tables ← _gel_all_team_tables(url)
    if tables == -1 then
        return -1
    end if
    Initialize empty dictionary dfs
    for all table in tables do
        df ← _get_dataframe(table)
        category ← table caption text before colon
        Add df to dfs[category]
    end for
    return dfs
end procedure
procedure _GEL_ALL_TEAM_TABLES(url)
    res ← Send HTTP GET request to url with timeout
    if ReadTimeout occurs then
        Sleep and retry
    end if
    soup ← Parse response with BeautifulSoup
    tables ← Find tables with class "stats_table"
    if tables is empty then
        return -1
    end if
    return tables
end procedure
procedure _GET_DATAFRAME(table)
    Read table HTML using pandas
    df ← First table from list
    Drop last column (e.g., Rk)
    Flatten headers if multi-index
    Reset index
    Drop columns: Age, Squad, Country, Comp, LgRank (if present)
    Convert all columns to numeric where possible
    return df
end procedure
procedure GET_LEAGUE_LEADERS
    res ← GET request to self.url
    soup ← Remove HTML comments and parse
    Find div with id "div_leaders"
    if div not found then
        return -1
    end if
    leaders ← All tables with class "columns"
    names ← Captions of leader tables
    Parse HTML tables using pandas
    Rename columns to Rank, Player, Value
    return Dictionary of leaders with names as keys
end procedure
```

performance evaluation. Algorithm 2 shows the algorithm for the Squad Stats Scraper.

3) Top Performers Scraper: The Top Performers Scraper extracts data related to the top performing players from Europe's top five leagues. The data includes information about the player with the most goals (number of goals, team name, player image link), the player with the most assists provided (number of assists provided, team name, player image link) and the goal keeper with the most clean sheets kept (number of clean sheets, team name, player image link). Algorithm 3 shows the algorithm for the Top Performers Scraper.

4) Player Stats Scraper: The Player Stats Scraper extracts player performance data. The data includes a wide range of performance metrics distributed in various categories. These include Standard Stats (appearances, minutes played, goals, and assists), Shooting (number of shots, shots accuracy, xG, xGoT), Passing (total passes, completion percentages, key passes), Pass Types (e.g. long passes, through balls, switches), Goal and Shot Creation metrics that capture both direct and indirect contributions to scoring opportunities, and Defensive Actions (tackles, interceptions, blocks). Possession-related (carries, touches, dribbles) as well as playing time (minutes per appearance, starting/substitution patterns) are also retrieved. This collection of scraper data allows the system to perform a detailed analysis of the contribution of a player throughout the season. Algorithm 4 shows the algorithm for the Player Stats Scraper.

5) TransferMarkt Scraper: Using the Transfermarkt scraper, the system is served with crucial off-field player metrics such as market value, injury status, and contract length, which are essential metrics consumed by the machine learning models for predicting the market prices of the players. Algorithm 5 shows the algorithm for the Transfermarkt Scraper.

C. Data Preprocessing

Data preprocessing is an integral part of the methodology as it provides the system with clean and accurate data. The data preprocessing pipeline was implemented as a multistep approach to ensure the reliability and usability of the data. First, data from Fbref.com and Transfermarkt.com were consolidated based on the player last name and age. In instances where the player last names were the same, the positions of players were taken into account for correct aggregation. Secondly, several values were missing or zero by default (e.g., xG for most goalkeepers). To tackle such discrepancies, any row with

Algorithm 3 Top Performers Scraper

Require: League name

Ensure: Dictionary of top scorer, top assister, and most clean sheets with images and teams

```
procedure FETCH_TOP_PERFORMERS(league)
    Initialize empty dictionary best_performers
    url ← league_links[league]
    response ← HTTP GET request to url with headers
    if response status code ≠ 200 then
        Print "Failed to fetch the page" and return
    end if
    soup ← Parse HTML with BeautifulSoup
    meta_block ← Find div with class "meta"
    paras ← Find all paragraph tags in meta_block
    for all paragraph p in paras do
        if p contains <strong>, <a>, and <span> then
            player ← Extract from <a>
            value ← Extract from <strong>
            team ← Extract from <span>
            if "Most Goals" in p then
                image ← IMAGE_GETTER(player)
                best_performers["Top Scorer"] ← [player, value, team, image]
            else if "Most Assists" in p then
                image ← IMAGE_GETTER(player)
                best_performers["Top Assister"] ← [player, value, team, image]
            else if "Most Clean Sheets" in p then
                image ← IMAGE_GETTER(player)
                best_performers["Clean Sheets"] ← [player, value, team, image]
            end if
        end if
    end for
    return best_performers
end procedure

procedure IMAGE_GETTER(player_name)
    normalized_name ← lower-case, hyphenated player_name
    search_url ← "https://fbref.com/en/search/search.fcgi?search=" + player_name"
    response ← HTTP GET request to search_url
    soup ← Parse HTML with BeautifulSoup
    if "Players from Leagues Covered" in soup text then
        search_results ← Find options in select tag
        for all option in search_results do
            if name in option matches player_name then
                player_url ← href of matching option
                response ← HTTP GET request to player_url
                soup ← Re-parse HTML
                break
            end if
        end for
    end if
    meta_div ← Find div with id "meta"
    media ← Find div with class "media-item" in meta_div
    if media contains image then
        return image URL
    else
        return None
    end if
end procedure
```

Algorithm 4 Player Stats Scraper

Input: `url` (FBref player URL), `stat` (optional)

Output: Processed player statistics as a DataFrame or dictionary of DataFrames

```
function AVAILABLESTATS
    return predefined list of stat categories
end function
function GETPLAYERSTATSFROMURL(url, stat)
    if stat not in AvailableStats() then
        Raise error
    end if
    table, rowCount ← EXTRACTTABLEFROMURL(url, stat)
    df ← FORMATDATAFRAME(table, rowCount, playerID)
    return df
end function
function GETALLPLAYERSTATSFROMURL(url)
    tables ← EXTRACTALLTABLES(url)
    if tables not found then
        return -1
    end if
    for all table in tables do
        if table's category in AvailableStats() then
            df ← FORMATDATAFRAME(table, rowCount, playerID)
            Add df to result dictionary
        end if
    end for
    return dictionary of DataFrames
end function
function FORMATDATAFRAME(table, rowCount, playerID)
    Parse HTML table to pandas DataFrame
    Drop unnecessary columns and rows
    Clean and convert data types
    Add playerID to DataFrame
    return cleaned DataFrame
end function
```

Algorithm 5 Transfrmarkt Scraper

```
Input: club_id, optional season_id
Format Transfermarkt URL using club_id and season_id
Request and load the webpage
if season_id is not provided then
    Extract it from the webpage
end if
Determine if club is for current or past season
for each player on the page do
    Extract:
    ID, Name, Position, Date of Birth, Age
    Nationality, Current Club, Height, Preferred Foot
    Joined On, Signed From, Contract Expiry
    Market Value, Status
end for
Store each player's data in a dictionary
Return dictionary with club_id, list of player dictionaries
```

TABLE I
GOAL KEEPERS

Name	Shot Stopping	EGP	CAC	SKA	Distribution
Alisson	2.20	-0.01	0.33	1.87	26.26
G. Donnarumma	2.52	-0.03	0.43	0.55	25.21
J. Oblak	2.42	-0.08	0.61	0.81	20.73
M. Maignan	2.51	-0.17	0.74	1.89	35.85
T. Courtois	1.91	-0.06	0.43	0.57	29.52

more than eight-five percent missing values was dropped, ensuring robustness of the dataset. In the remaining dataset, numerical values were imputed using the median where the absence of values was insignificant. As the final step, the data on age and market values was put through the statistical technique called as winsorization to limit the impact of outliers in the data. It was found that winsorization had an impact on the final results and normalizing the data for players too old or too young aided in standardizing the data.

1) Feature Engineering: As part of the feature engineering process, the dataset was divided into ten classes - goalkeepers (GK), left backs (LB), right backs (RB), center backs (CB), center defensive midfielders (CDM), center midfielders (CM), center attacking midfielders (CAM), left wingers (LW), right wingers (RW), and center forwards (CF) . For each class, customized metrics were developed using the preprocessed data. The metrics were as follows:

1. Goalkeepers (GK): The following metrics quantify the on-field performances for goalkeepers.

a. Shots Saved: The shot stopping ability of goalkeepers per 90 minutes was calculated using the formula:

$$\text{Shot Stopping} = \frac{\text{Saves}}{90\text{s}} \tag{1}$$

b. Expected Goals Prevention (EGP): This custom metric quantifies the goals prevention performance of goalkeepers per 90 minutes played.

$$\text{Expected Goals Prevention} = \frac{PSxG + GA}{90s} \tag{2}$$

c. Cross and Aerial Control (CAC): Shows how well the goalkeeper performs at catching or punching crosses coming into the 16 yard box per 90 minutes played.

$$\text{Crosses Stopped} = \frac{\text{Stp}}{90\text{s}} \tag{3}$$

d. Sweeper Keeper Activity (SKA): Quantifies the goalkeeper's ability to perform sweeping actions outside the 16 yard box per 90 minutes played.

$$\text{Sweeping Ability} = \frac{\text{\#OPA}}{90\text{s}} \tag{4}$$

e. Distribution Ability: Shows how capable the goalkeeper is distributing the ball with their feet. Calculated per 90 minutes played.

$$\text{Distribution Ability} = \frac{Cmp + KP + FinalThird}{90s} \tag{5}$$

2. Center Backs (CB): The following metrics quantify the on-field performances for center backs. Table II displays a subset of the center backs dataset.

a. Defensive Actions: Custom metric showing the center back's defensive contribution on the field per 90 minutes played.

$$\text{Defensive Contribution} = \frac{Tkl + Int + Blocks + Clr + Recov}{90s} \tag{6}$$

b. Aerial Ability: Quantifies the aerial solidity of the center back per 90 minutes played.

$$\text{Aerial Ability} = \frac{Won}{90s} \tag{7}$$

c. Passing Ability: Shows how well the center back passes the ball and progresses the ball up field per 90 minutes played

$$\text{Passing Ability} = \frac{Cmp + KP + PrgP}{90s} \tag{8}$$

d. Positioning and Defensive Awareness: Quantifies the positional awareness of the center back on field per 90 minutes played.

$$\text{Positioning and Defensive Awareness} = \frac{Blocks + Clr}{90s} \tag{9}$$

e. Disciplinary Record: Shows how disciplined the center back is across the games. Calculated per 90 minutes played.

$$\text{Discipline} = \frac{CrdY + CrdR + 2CrdY + Fouls}{90s} \tag{10}$$

TABLE II
CENTER BACKS

Name	Def. Actions	Aerial Duels	Passing	Def. Aware.	Discipline
Marquinhos	12.43	4.07	13.85	4.80	1.15
P. Cubarsí	8.11	2.72	11.35	3.37	0.70
P. Torres	8.02	2.32	9.25	3.60	0.40
V. van Dijk	11.55	2.45	8.02	5.68	0.51
W. Saliba	10.98	2.43	8.08	3.83	1.10

3. Full Backs (LB and RB): The following custom metrics have been used to quantify the performances of left backs and right backs. Table III displays a subset of the full backs dataset.

a. Defensive Duties: Quantifies how well the full back contributes defensively to the team, per 90 minutes played.

$$\text{Defensive Duties} = \frac{Def3rd, Int, Blocks, Clr, Recov}{90s} \tag{11}$$

b. Offensive Contributions: Quantifies how well the full back contributes offensively to the team, per 90 minutes played.

$$\text{Offensive Contributions} = \frac{PrgC + PrgP + KP + xA}{90s} \tag{12}$$

c. Final Third Play: This custom metric shows how well the full back makes themselves available to contribute in the final third, per 90 minutes played.

$$\text{Final Third Play} = \frac{Crs + SCA + CPA + PPA}{90s} \tag{13}$$

d. Possession Play: Quantifies how well the full back take cares of the ball on their feet, per 90 minutes played

$$\text{Possession Play} = \frac{Att3rd\_possession + TotDist}{90s} \tag{14}$$

e. Dribbling Accuracy: Measures how well the player dribbles through the opposition's press.

$$\text{Dribbling Accuracy} = \frac{Succ}{90s} \tag{15}$$

4. Central Defensive Midfielders (CDM): The following custom metrics have been used to quantify the performances of center defensive midfielders.

TABLE III
FULL BACKS

Name	Att. Contributions	Final Third	Possession	Dribbling
A. Balde	9.24	8.29	29.83	0.43
A. Robertson	10.69	9.68	32.86	0.04
D. Udogie	9.48	3.56	26.86	0.11
F. Dimarco	7.41	14.59	35.74	0.03
F. Mendy	4.61	0.71	21.42	0.03

TABLE IV
CENTER DEFENSIVE MIDFIELDERS

Name	Def. Work	Passing	Build-Up	Recoveries	Line Breaking
B. Guimarães	10.26	3.07	22.80	5.98	13.75
Casemiro	17.54	6.53	24.28	6.80	11.14
G. Xhaka	9.33	3.71	37.14	5.57	23.84
J. Neves	13.41	5.73	26.61	7.46	16.13
Y. Bissouma	12.95	7.32	21.00	6.63	10.24

TABLE V
CENTER MIDFIELDERS

Name	Passing	Dribbling	Def. Work	Chance Creation	Possession
D. Rice	11.26	4.13	9.56	4.17	54.04
F. Valverde	13.30	2.67	10.72	2.91	67.67
Pedri	18.64	4.20	12.43	4.92	75.93
Vitinha	2.19	4.66	8.66	3.16	15.71

TABLE VI
CENTRAL ATTACKING MIDFIELDERS

Name	Playmaking	BP	FTI	Goal Threat	FBE
D. Olmo	7.76	9.11	31.22	1.4	0.79
F. Wirtz	9.52	11.44	51.39	1.09	1.15
Isco	13.09	10.2	34.3	1.22	0.6
Ju. Bellingham	8.44	10.10	27.15	1.11	0.58
X. Simons	7.69	9.62	29.75	0.75	0.78

TABLE VII
WINGERS

Name	Dribbling	CAP	Goal Threat	FTI
Bukayo Saka	10.07	7.82	0.89	42.62
Ousmane Dembélé	12.51	5.56	3.07	48.25
Rodrygo	9.39	4.02	0.72	41.80
Raphinha	6.39	7.80	1.73	38.85

a. Defensive Contributions:

$$\text{Defensive Contributions} = \frac{Tkl + Int + Blocks + Clr + Recov}{90s} \tag{16}$$

b. Passing Ability:

$$\text{Passing Ability} = \frac{Cmp}{90s} \tag{17}$$

c. Build-Up Play:

$$\text{Build-Up Play} = \frac{xA + xAG + Ast + PrgDist}{90s} \tag{18}$$

d. Ball Recovery & Defensive Work:

$$\text{Ball Recovery \& Defensive Work} = \frac{Recov + Int}{90s} \tag{19}$$

e. Line Breaking Passes:

$$\text{Line Breaking Passes} = \frac{KP + PrgP + \text{1/3\_passing}}{90s} \tag{20}$$

5. Central Midfielders (CM): The following custom metrics have been used to quantify the performances of center midfielders.
a. Passing and Vision: Quantifies the how well the center midfielders passes the ball to contribute in offensive phases of the play, per 90 minutes played

$$\text{Passing} = \frac{PrgP + \text{1/3\_passing}}{90s} \tag{21}$$

b. Dribbling: Shows how well the center midfielder takes care of the ball and dribbles past opponents, per 90 minutes played.

$$\text{Ball Carrying} = \frac{Succ + PrgC + CPA}{90s} \tag{22}$$

c. Defensive Work: Explains the contribution of the center midfielder in defence, per 90 minutes played.

$$\text{Defensive Work} = \frac{Tkl + Int + Blocks + Clr + Recov}{90s} \tag{23}$$

d. Chance Creation: Quantifies the creative qualities of the center midfielder.

$$\text{Chance Creation} = \frac{SCA + xG + xA + xAG}{90s} \tag{24}$$

e. Possession Retention: Shows the ability of the center midfielder to retain the ball and not concede possession to the opposition, per 90 minutes played.

$$\text{Possession Retention} = \frac{Cmp + KP + \text{1/3\_passing} + Succ}{90s} \tag{25}$$

6. Central Attacking Midfielders (CAM): The following custom metrics have been used to quantify the performances of central attacking midfielders.
a. Creativity and Playmaking: Quantifies the creativity of the central attacking midfielder, per 90 mintutes played.

$$\text{Playmaking} = \frac{xA + SCA + \text{1/3\_passing}}{90s} \tag{26}$$

b. Ball Progression (BP): Numerifies the ability of the central attacking midfielder to move the ball up-field, per 90 minutes played.

$$\text{Ball Progression} = \frac{PrgP + PrgC}{90s} \tag{27}$$

c. Final Third Impact (FTI): Shows how much the central attacking midfielders impacts the game in the final (attacking) third, per 90 minutes played.

$$\text{Final Third Impact} = \frac{Att3rd\_possession + CPA + PPA}{90s} \tag{28}$$

d. Goal Threat: This metric shows the central attacking midfielder's ability to score goals, per 90 minutes played.

$$\text{Goal Threat} = \frac{xG + npxG + Gls}{90s} \tag{29}$$

e. Final Ball Efficiency (FBE): The ability of the central attacking midfielder to deliver the final ball, per 90 minutes played.

$$\text{Final Ball Efficiency} = \frac{xA + xAG + PPA}{90s} \tag{30}$$

7. Wingers (LW and RW): The following custom metrics have been used to quantify the performances of wingers. **a. Dribbling and Ball Carrying:** Shows how well the winger is at dribbling the ball past opponents, per 90 minutes played.

$$\text{Dribbling} = \frac{Succ + PrgC + CPA}{90s} \tag{31}$$

b. Crossing and Playmaking (CAP): This metric quantifies the playmaking and crossing ability of the winger, per 90 minutes played.

$$\text{Crosses and Playmaking} = \frac{xA + xAG + Crs}{90s} \tag{32}$$

c. Goal Threat (GT): This metric shows the winger's ability to score goals, per 90 minutes played.

$$\text{Goal Threat} = \frac{xG + npxG + Gls}{90s} \tag{33}$$

d. Final Third Involvement (FTI): Shows how much the winger impacts the game in the final (attacking) third, per 90 minutes played.

$$\text{Final Third Impact} = \frac{Att\_3rd\_possession + CPA + PPA}{90s} \tag{34}$$

8. Center Forwards (CF): The following custom metrics have been used to quantify the performances of center forwards.

TABLE VIII
CENTER FORWARDS

Name	GT	Ch.Conv.	LUP	Shooting Accuracy	PBP
E. Haaland	2.18	0.05	4.12	2.06	6.20
H. Kane	2.36	0.07	7.05	1.73	6.07
K. Mbappé	2.02	0.05	14.00	2.25	9.70
L. Martínez	1.35	0.03	7.54	1.32	5.56
R. Lewandowski	2.76	0.08	5.66	1.65	5.96

a. Goal Threat (GT): This metric shows the center forward's ability to score goals, per 90 minutes played.

$$\text{Goal Threat} = \frac{xG + npxG + Gls}{90s} \tag{35}$$

b. Chance Conversion : Quantifies how efficient is the center forward at converting chances, per 90 minutes played

$$\text{Chance Conversion} = \frac{G - PK + xG}{90s} \tag{36}$$

c. Link-up Play (LUP): Shows how well the center forward links up with the team through passing the ball, per 90 minutes played.

$$\text{Link-Up Play} = \frac{PrgR + xA + PPA}{90s} \tag{37}$$

d. Shooting Accuracy: Shows how accurately does the center forward shoot the ball on goal, per 90 minutes played.

$$\text{Shooting Accuracy} = \frac{SoT + Sh}{90s} \tag{38}$$

e. Penalty Box Presence (PBP): Quantifies the how present the center forward is in the penalty box, per 90 minutes played.

$$\text{Penalty Box Presence} = \frac{Att\_Pen}{90s} \tag{39}$$

D. Machine Learning Models

This section presents the proposed architecture of the machine learning model along with the parameters and rationale behind the selected models.

1) Dimensionality Reduction: To avoid overfitting, which is often introduced with high-dimensional data, PCA was performed after cleaning and feature engineering. This preprocessing reduced some dimensionality and highly correlated data, ensuring that the principal components identified by PCA were robust and effectively captured the variance.

- The Elbow Method (Scree Plot) explains the variance versus the number of components in a range (x, y).

To better understand the workings behind PCA, the mathematical formulas governing PCA are provided below.

Given a standardized dataset $\mathbf{X} \in \mathbb{R}^{n \times d}$, where n is the number of samples and d is the number of features, the covariance matrix is computed as:

$$\mathbf{C} = \frac{1}{n-1}\mathbf{X}^\top \mathbf{X} \tag{40}$$

Eigenvalue decomposition is then performed on the covariance matrix:

$$\mathbf{C}\mathbf{v}_i = \lambda_i \mathbf{v}_i \tag{41}$$

where λ_i is the eigenvalue corresponding to the eigenvector $\mathbf{v}_i$. The eigenvectors are sorted in descending order of their eigenvalues.

Let $\mathbf{V}_k \in \mathbb{R}^{d \times k}$ be the matrix of the top k eigenvectors. The data is then projected onto the new k-dimensional subspace as[14]:

$$\mathbf{Z} = \mathbf{X}\mathbf{V}_k \tag{42}$$

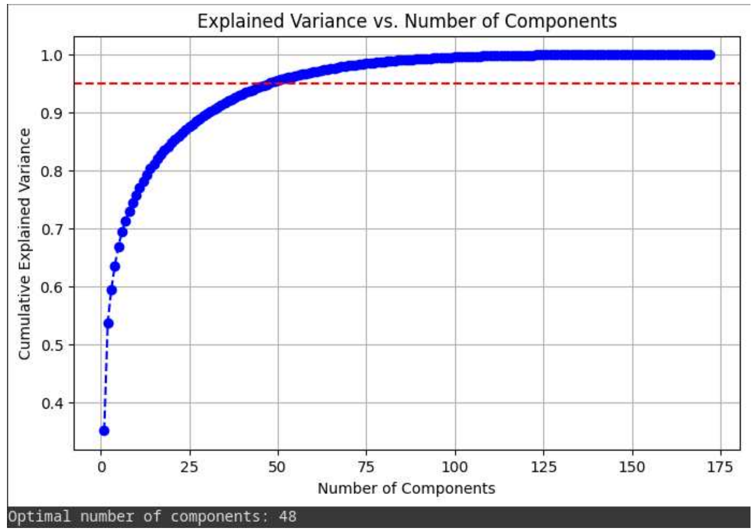

Fig. 2. PCA Scree Plot

Here, $\mathbf{Z} \in \mathbb{R}^{n \times k}$ is the transformed feature matrix in the reduced-dimensional space.

Following PCA, the transformed data are passed into an SEM, a stacked ensemble model, which performs the prediction of the market value of a player.

E. Stacked Ensemble Modeling

In recent times, multiple meta-heuristic learners and optimization algorithms have been doctored in the domain of football analytics [15]. This paper presents a novel approach among those to predict the market value of a football player, based on real data, compared to the FIFA values used by many other studies.

Stacking is an ensemble approach that uses a 2-level approach, level-0 base learners and a level-1 meta learner. The level-1 meta learner is an aggregator that receives the output from single-based learners.

a) Base Learners: The base learners used are selected to capture linear and non-linear relationships in the data. Both parametric and non-parametric models were selected.

Linear Learners

- **Ridge Regression**: Also called Tikhonov regularization, it is used in ill-posed problems, useful to mitigate the problem of multicollinearity in regression problems, caused by a high dimensionality. It is useful in this study due to large number of principal components(¿40). It employs L_2 regression to control multilinearity. Ridge regression minimizes the following loss function[16]:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda \|\beta\|_2^2 \right\} \tag{43}$$

- **Lasso Regression**: Lasso Regression is a statistical operator that penalizes the model to prevent overfitting and enhance accuracy. It does so by shrinking some coefficients to zero, effectively excluding them from the model. It employs L_1 regression for automation feature selection.
  Lasso regression introduces an L_1 penalty to promote sparsity [17]:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda \|\beta\|_1 \right\} \tag{44}$$

- **ElasticNet**: ElasticNet combines both, Lasso and Ridge regression, which improves its ability with regards with reconstruction. ElasticNet combines both L_1 and L_2 penalties[18]:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \|\mathbf{y} - \mathbf{X}\beta\|^2 + \lambda_1 \|\beta\|_1 + \lambda_2 \|\beta\|_2^2 \right\} \tag{45}$$

Tree-Based Learners

- **Random Forest Regressor**: Random forest regression is a machine learning technique that uses multiple decision trees to predict continuous values using the bootstrap averaging method on the outputs given by each tree. It is included for its ability in smoothing out the errors from other learners, in the overall stacking architecture, while effectively capturing non-linear dependencies.
- **XGBoost**: By leveraging a magnitude of decision trees, it focuses on creating a powerful predictive model by using an iterative process that focuses on minimizing errors. XGBoost is proved to be unbeatable for handling structured data, along with its ability to address class imbalance, which was crucial in our study, due to the limited data of goalkeepers compared to other positions.
- **LightGBM**: LightGBM is designed specifically for large-scaled data, and employs a leaf-wise growth strategy, opposed to the level-based growth strategy used by other tree based algorithms. This allows it to have deeper trees and better predictive ability.
- **Gradient Boosting Regressor**: Similar to XGBoost, it builds the model iteratively.
- **AdaBoost Regressor**: AdaBoost is often used in conjunction with other machine learning algorithms to improve performance. The output of multiple weak learners is combined into a weighted sum that represents the final output of the model [19]
- **Support Vector Regression (SVR)**: SVR tries to find a function that is able to accurately predict the continuous output value for any given output value. It uses both linear and non linear kernel.

1) Meta Learner: The meta learner, also known as the Level-1 learner, is the final model that receives the output from all the base models, and predicts the market value by using the stacking ensemble algorithm. This study uses the Random Forest Regressor as the meta learner. A common strategy to train a stacking model is to use a hold-out set, where the dataset is split into two parts - the first layer is trained using the first part of the dataset, and the second layer is given the second set of data. The output from the meta model is used to create a new dataset, which makes this new dataset a 3D dataset. This new dataset ensures that the model learns the target value, given the inputs from the first layer. The rationale behind using the Random Forest in both base learners and as a meta learner is to use its ability to generalize well, and smoothen the results, and helps capture the complex relationships. As a base learner, it introduces diversity, and as a meta learner, its insensitivity to multicollinearity makes it a strong candidate to be used in both the layers.

The mathematical representation for the proposed model is given as:

$$\hat{y} = f_{\text{meta}}\left(f_1(\mathbf{Z}), f_2(\mathbf{Z}), \ldots, f_m(\mathbf{Z})\right) \tag{46}$$

a) Where::

- $\hat{y}$: Final prediction (market value)
- $f_1, f_2, \ldots, f_m$: Base learners (e.g., Ridge, Lasso, RF, XGBoost, etc.)
- $\mathbf{Z} \in \mathbb{R}^{n \times k}$: PCA-reduced feature matrix with n samples and k components
- f_{meta}: Meta learner (Random Forest Regressor)

To evaluate the performance of the final SEM, multiple regression metrics were computed on both training and test sets. The rationale behind computing both training and testing sets was to check for overfitting. The difference between the training and test sets is a great metric to understand the state of the model. The higher the difference between these, the more the model overfits or underfits. The model achieved an R^2 score of 0.9464 on the training set and 0.9457 on the test set. The other metrics are shown in table 1.

Metric	Train	Test
R^2 Score	0.9464	0.9457
Mean Squared Error (MSE)	9.73×10^{13}	9.69×10^{13}
Root Mean Squared Error (RMSE)	3,119,656.30	3,112,937.64
Mean Absolute Error (MAE)	2,199,469.47	2,259,460.70
Cross-Validation R^2 (Mean $\pm$ Std)		0.9383 ± 0.0029

TABLE IX
EVALUATION METRICS FOR THE STACKING ENSEMBLE MODEL

The cross validation R^2 score being close to the R^2 score of train and test sets proves that the model does the overfit, and the combination of chosen base learners and meta learners is a great fit for the type of data this study deals with.

IV. Conclusion and Future Work

By efficiently automating data extraction and processing of advanced player statistics from robust and vast data sources such as Fbref and Transfermarkt, the proposed system uses the extracted data to not only automate the manual and subjective process of scouting football players, but also drive the decision making process of coaches and managers. The system leverages complex machine learning models for predicting the market value predictions, along with clustering algorithms to identify players that are similar both, tactically and stylistically. The system includes role-specific metrics and performs position-aware analysis. Additionally, the usage of detailed visualizations such as radar charts and other performance graphs, makes the data analysis interpretable and actionable for coaches.

The system provides a robust framework to find replacements for football players, there are several aspects that exist for future enhancements. In the future, we would like to work on integrating match-by-match real time performance data which would offer dynamic tracking of players on the field. Additionally, building an all-inclusive analysis hub by including video analytics and sentiment analysis of players from media sources. Finally, expanding our databases to retired players, women's leagues and youth leagues would open underexplored doors.

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