# AN INTELLIGENT MOBILE APPLICATION FOR SPORTS RECOMMENDATIONS AND PERFORMANCE PREDICTION USING OPEN AI AND MACHINE LEARNING

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***ABSTRACT***

*This research focuses on the development of an intelligent mobile application to address challenges in selecting suitable sports and predicting athletic performance. The problem of early dropout in youth sports and performance stagnation due to mismatched expectations underscores the need for solutions. The proposed application combines OpenAI and machine learning algorithms to evaluate user inputs, including physical attributes, psychological traits, and environmental factors, to recommend appropriate sports and predict future performance. Key technologies include generative AI for personalized sports recommendations and machine learning algorithms for performance prediction in golf, trained on professional player data. Challenges such as data accuracy, generalization of algorithms, and prompt optimization were tackled through user feedback and rigorous performance testing. The use of accuracy measurement validated the system's reliability and adaptability, demonstrating its usefulness. By offering accurate and scalable solutions, the application has the potential to create sustained athletic engagement and enhance decision-making for users across.*

***KEYWORDS***

*Open AI, Machine Learning, Flutter, Sports Recommendation*

## 1. INTRODUCTION

For many individuals, selecting a sport that aligns with their talents and physical condition is a significant challenge. This difficulty often arises from intrapersonal constraints, such as physical limitations, interpersonal factors like parental pressure, and structural barriers, including inadequate facilities [1]. These challenges contribute to a high dropout rate among young athletes, with approximately 90% of boys and 75% of girls quitting organized sports within the first five years of participation [2].

As competition in sports intensifies, the need to choose a suitable sport early on becomes increasingly important. This decision can overwhelm parents who must navigate numerous options for their children. Even for those who continue participating in sports, challenges persist. Athletes often struggle with a mismatch between their perceived improvement methods and their actual performance, creating unrealistic expectations [3]. When these expectations are unmet,

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mental strain can arise, exacerbated by self-imposed or parental pressure, fostering a destructive environment within competitive sports [4].

The methodologies reviewed highlight different approaches to addressing challenges in sports recommendations and performance predictions. Each aimed to create in their own method to solve its targeted issue and provide actionable insights but faced significant limitations in scope and adaptability. Some focused heavily on specific attributes, such as physical traits, while neglecting psychological or contextual factors. Others prioritized performance prediction but were limited to professional athletes or single sports, lacking generalization for broader applications. These existing solutions often struggled with integrating diverse data types or adapting to amateur athletes and multiple sports. In contrast, this project leverages generative AI and machine learning to address these gaps. It considers a holistic aspect in regards to physical, psychological, and environmental, ensuring personalized recommendations and accurate performance predictions across various sports and user levels. This broader and more adaptive approach builds on prior methodologies to offer a more comprehensive and scalable solution.

Through the integration of OpenAI and machine learning, this mobile analytical application addresses two distinct problems: recommending the most suitable sports for individuals and predicting athletic performance.

The application uses OpenAI to generate personalized sports recommendations by evaluating a comprehensive 3 sets of inputs, physical abilities, psychological traits, and preferences. Previous research on sports suitability has often been narrow in scope, focusing solely on user preferences or physical talents in children [5][6]. These methods lack the depth to holistically assess suitability. By utilizing OpenAI's capabilities, this application provides accurate and tailored recommendations, addressing gaps in existing methodologies.

On a separate front, the application employs machine learning algorithms to predict athletic performance. Specifically, it analyzes users' sub-skill levels—such as putting in golf—and projects future performance. Past research in performance prediction has predominantly targeted professional athletes, focusing narrowly on specific skills or geographic conditions [7]. Unlike these efforts, this application integrates a broader range of skills to deliver more accurate and actionable predictions, making it applicable to amateur and youth athletes.

This dual approach not only helps users select sports that align with their abilities but also reduces mental strain by offering realistic expectations and identifying areas for improvement. While the current focus is on golf, the application aims to expand to other sports, providing a scalable solution for both sports suitability and performance prediction.

The experiments aimed to evaluate the accuracy and reliability of the sports recommendation and performance prediction systems, which are vital to the application's functionality. The first experiment assessed ChatGPT's ability to recommend suitable sports by analyzing user data categorized into physical, psychological, and general attributes. Its recommendations were compared against the actual sports pursued by professional and collegiate athletes, serving as a benchmark for accuracy.

The second experiment focused on testing the performance prediction algorithms by comparing models such as linear regression, neural networks, random forest and other models. These models were trained on professional athlete data and evaluated using R^2 and MSE. Neural networks demonstrated the ability to measure complex interactions among variables, while linear regression offered simpler, but also precise predictions. Therefore, the integrated use of both helped to increase the accuracy overall for this application.

## 2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

### 2.1. Ensuring the Accuracy

One significant challenge in implementing the sports recommendation component is ensuring the accuracy of OpenAI's outputs. Although generative AI generally provides reliable evaluations, inconsistencies could arise due to limitations in the training data or the specificity of the inputs, the prompt [8]. To address this, two strategies could be employed. First, professional athletes' data could be used as a benchmark; if the AI reliably recommends sports aligned with these athletes' careers, it demonstrates its effectiveness. Second, user feedback could be collected over time to assess the long-term accuracy of recommendations. Tracking users' continued engagement and satisfaction with AI-suggested sports would help refine its outputs and validate its reliability.

### 2.2. The Data Difference

A significant challenge in performance prediction for golf lies in adapting professionally collected data to accurately represent players across all skill levels [9]. Since the AI model is trained primarily on data from professional athletes, its predictions may not align with the performance patterns of amateur players. To address this, the application could establish a standard for course difficulty based on factors like distance and slope rating, tailored to the conditions professional players typically encounter. For amateur players, a similar standard could be developed using smaller sample sets collected over time or online. These adjustments would help calibrate the AI model, ensuring it accounts for varying skill levels and course difficulties, thereby improving prediction accuracy for diverse users.

### 2.3. Ensuring the Consistency

Another challenge in the sports recommendation component is ensuring the consistency of the fitness scores generated during the recommendation process. Each score is derived from analyzing the user's input across various attributes such as physical, psychological, and preference where each will receive various scores. The score reflects how well-suited the user is to each recommended sport. However, ensuring that this score remains accurate and consistent is difficult without a reliable baseline for comparison. To address this, I could create an initial baseline using data from existing studies or average values across key metrics. Over time, user-generated data from the app would refine this baseline, improving the reliability and consistency of the scores provided during the recommendation process.

## 3. SOLUTION

The application is structured around three primary components: the user interface, the sports recommendation system, and the machine learning-based performance prediction module. These components work together seamlessly to deliver a comprehensive user experience.

The program begins with the user interface (UI), developed using Flutter, which provides an intuitive and accessible platform for users to interact with the application [10]. Through the UI, users can view recorded data, analyze their sports-related performance, and access various features. This includes logs of recommended sports, skill evaluations, and body-related metrics, ensuring users have all relevant information readily available.

The sports recommendation system is the next critical component. Users input data related to their physical attributes, psychological traits, and general conditions [11]. This information is sent via an API to ChatGPT, accompanied by a detailed prompt. The AI analyzes the data and returns outputs such as physical and psychological scores and recommended sports, enabling tailored suggestions that align with the user's unique profile.

The performance prediction module, focused initially on golf, uses machine learning to forecast future performance. Developed in Python, the model is trained on over 1,000 PGA professional player datasets sourced from pgatour.com. After cleaning and processing this data, it is fed into multiple algorithms including linear regression and neuron network  to generate predictions based on user input. Due to the challenge in integrating directly to flutter, this module relies on a Flask backend to process data from Flutter, run the model, and return the predictions to the app.

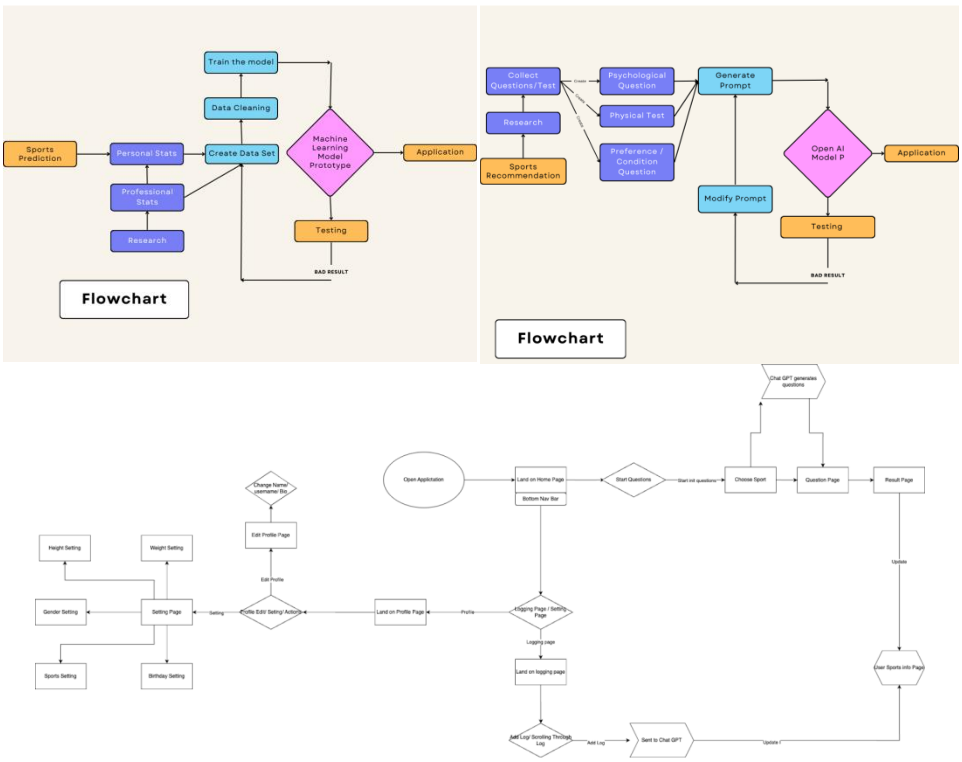



Figure 1. Overview of the solution

The user interface (UI) is integral to the organization and accessibility of the application, ensuring users can seamlessly interact with its features. Its primary purpose is to provide an intuitive platform for inputting data, accessing analyses, and navigating between key functionalities, such as the sports recommendation system and performance prediction module [12].

Developed using Flutter, the UI offers a visually appealing and responsive experience across devices. One particularly important page within the UI is the settings page, which stores critical user information, such as body attributes. This design choice allows each piece of information to be individually stored in shared preferences, a system that makes it accessible for further analysis by other components of the application [13].

By compartmentalizing user data, the settings page enhances the organization and scalability of the application. Each data point can be updated or added independently, which simplifies future modifications and improves the efficiency of data processing. For instance, the information stored here is used to analyze users' progress in their chosen sport or evaluate their potential suitability for new sports.

In the broader context of the program, the UI acts as the bridge between users and the application's advanced systems, ensuring a smooth flow of interaction while maintaining flexibility for expansion.

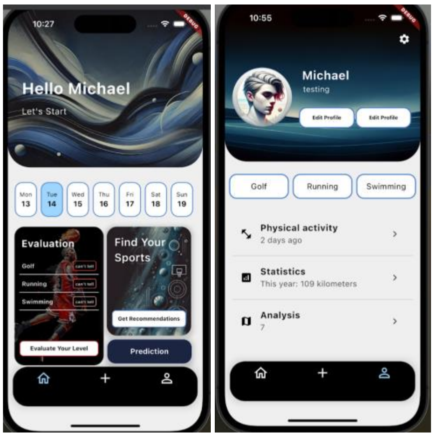



Figure 2. Screenshot of the user page

Figure 3. Screenshot of code 1

The code shown represents the Home Screen of this application, designed to provide users with a central hub for navigation and interaction. The code uses Flutter's CustomScrollView with a SliverAppBar, which enables a dynamic app bar that expands and collapses based on scrolling behavior. This adds to the design of this application, making it visually appealing and organized as the user opens the club. The FlexibleSpaceBar is utilized to display a customizable background image with a gradient overlay, further enhancing the visual appeal.

The Container inside the FlexibleSpaceBar applies designs that include background images (loaded from assets). The SafeArea widget ensures the content stays within the device's usable screen space. Below the app bar, widgets such as Text, Column, and Row manage structured layouts, including personalized greetings, date selection, and evaluation and prediction options.
The code sets up user navigation to key app functionalities like sports recommendations and performance predictions. Each button redirects users to respective screens or API endpoints for further interaction. This component acts as the gateway to other features, linking users with the app's primary functionalities.

The sports recommendation system focuses on solving the challenge of helping users identify sports that best suit their individual abilities and preferences. This component leverages OpenAI's ChatGPT through an API connection, which acts as the backbone for generating tailored recommendations. The system begins by gathering user inputs through required tests and questionnaires, which are categorized into three primary attributes: physical attributes, psychological attributes, and general conditions [11] . For example, the system evaluates physical attributes such as hand-eye coordination or endurance, while psychological attributes may include traits like focus or resilience. Upon evaluation, a score will be outputted for each categorical attribute. These scores will then be analyzed and combined for an final output of a set of suitable sports for the user.

The API key plays a critical role in this integration from Flutter to OpenAi—it is a unique identifier assigned to authenticate the application's access to OpenAI's servers. The key ensures that only authorized systems can make requests to the API, protecting data security and managing usage [14].

When the application sends data to the OpenAI API, it includes the API key as part of the HTTP request header. The header also contains a bearer token, which adds an additional layer of security by encrypting the API key during transmission. This token ensures that sensitive information remains protected from unauthorized access.

Once the request is made, the API processes the user's data using a structured prompt tailored to the application's needs. The prompt is designed to guide ChatGPT in interpreting the user's input and categorizing it into actionable insights. This structured interaction between the application and the OpenAI API allows for the generation of accurate and personalized results [15].

By combining detailed data organization with secure API integration, the sports recommendation system delivers reliable sports suggestions.

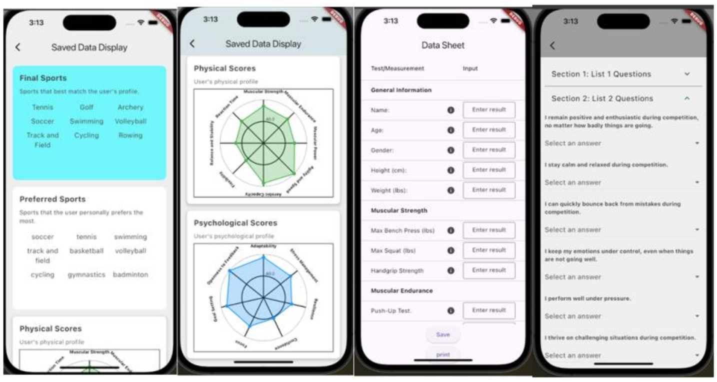



Figure 4. Screenshot of saved data

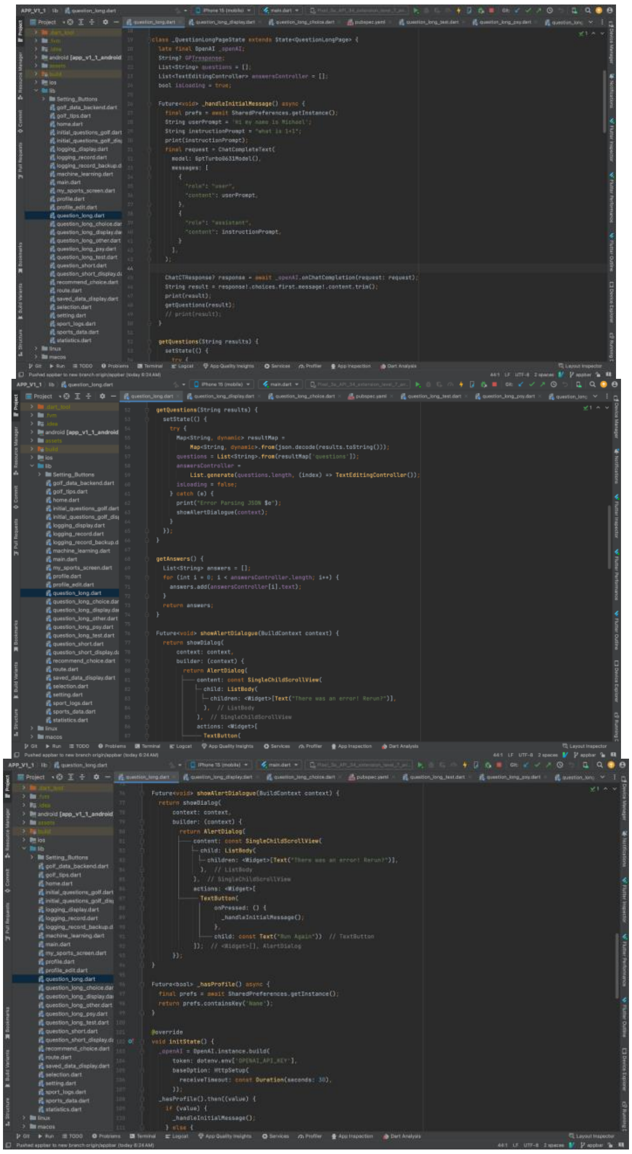


Figure 5. Screenshot of code 2

This component integrates OpenAI's ChatGPT API to provide personalized sports recommendations. It processes user inputs such as physical, psychological, and general attributes, and generates tailored suggestions using a structured prompt. The handleInitialMessage() method initializes communication with ChatGPT, sending a predefined prompt that includes user-provided data. The API request uses the ChatCompleteText function, specifying the GPT Turbo 0631 Model for efficient processing.

The server processes the prompt and returns a JSON response containing the recommended sports. The getQuestions() function parses this response, mapping it to a structured format and dynamically generating text fields for user interaction. Any errors during the process trigger an alert dialog, prompting users to rerun the query.

By using the ChatGPT API, this system ensures dynamic adaptability and personalization. This connection is initialized during the initState() function, where the API key is retrieved from environment variables, maintaining security while enabling integration with OpenAI.

The performance prediction system is designed to accurately project a user's current skill level and predict future performance in sports, with a focus on providing actionable insights for improvement. This component uses a dual-layered approach, combining linear regression and neural network algorithms, to deliver precise predictions based on the user's skill data. The algorithms were developed using Python3, with Flask serving as the backend framework to integrate the model into the application.

The system first uses a linear regression model to analyze the user's performance in specific skillsets, such as putting accuracy in golf or shot precision in basketball. The regression model calculates the linear relationship between the user's input variables (physical metrics or past scores) and their projected performance for individual skillsets [16][17]. The mathematical representation of the regression model is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Where:

- $Y$: Predicted suitability score for a sport.
- $X_1, X_2, \ldots, X_n$: User input variables (e.g., physical and psychological attributes).
- $\beta_0$: Intercept (baseline suitability without any specific attributes).
- $\beta_1, \beta_2, \ldots, \beta_n$: Coefficients representing the impact of each attribute on suitability.
- $\epsilon$: Error term accounting for variability not explained by the model.

After predicting performance on individual skillsets using linear regression, the system integrates these results into a neural network model to compute an overall performance score. The neural network captures complex, non-linear interactions between different skillsets, providing a more holistic projection of the user's capabilities [18]. The network comprises multiple layers, including input, hidden, and output layers, and uses activation functions to model intricate patterns in the data [19].

The algorithms were trained on a dataset of over 1,000 professional player records, collected from sources such as pgatour.com for golf. The data was preprocessed through cleaning and normalization to remove inconsistencies and standardize the input variables. During training, the system employed cross-validation to ensure that the models generalized well to new data. The combined approach of regression and neural networks demonstrated an overall prediction accuracy exceeding 90%.

To assess the effectiveness of the models, the following metrics were utilized:

Mean Squared Error (MSE): Measures the average squared difference between observed and predicted scores for both skill-specific and overall performance predictions [20][21].

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Where:

- $Y_i$: Observed suitability score for the $i$-th sport.
- $\hat{Y}_i$: Predicted suitability score for the $i$-th sport.

2. R-squared (R^2): Evaluates the proportion of variance in the performance scores explained by the models. Higher R^2 values indicate better fit [22].

$$R^2 = 1 - \frac{\mathrm{SS}_{\mathrm{residual}}}{\mathrm{SS}_{\mathrm{total}}}$$

Where:

- $\mathrm{SS}_{\mathrm{residual}}$: Sum of squared differences between observed and predicted $Y$.
- $\mathrm{SS}_{\mathrm{total}}$: Total sum of squared differences from the mean of $Y$.

The Flask backend facilitates seamless communication between the prediction algorithms and the application. User data is sent to the backend via APIs, processed through the models, and the results are returned to the app's frontend.

By combining advanced regression and neural network techniques, the performance prediction system delivers accurate, actionable forecasts of user performance. This allows users to set realistic goals, focus on areas for improvement, and track their progress over time.

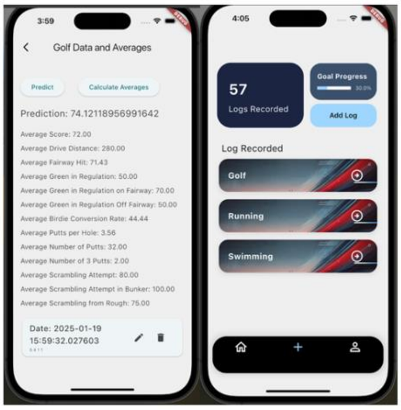



Figure 6. Screenshot of alcohol consumption

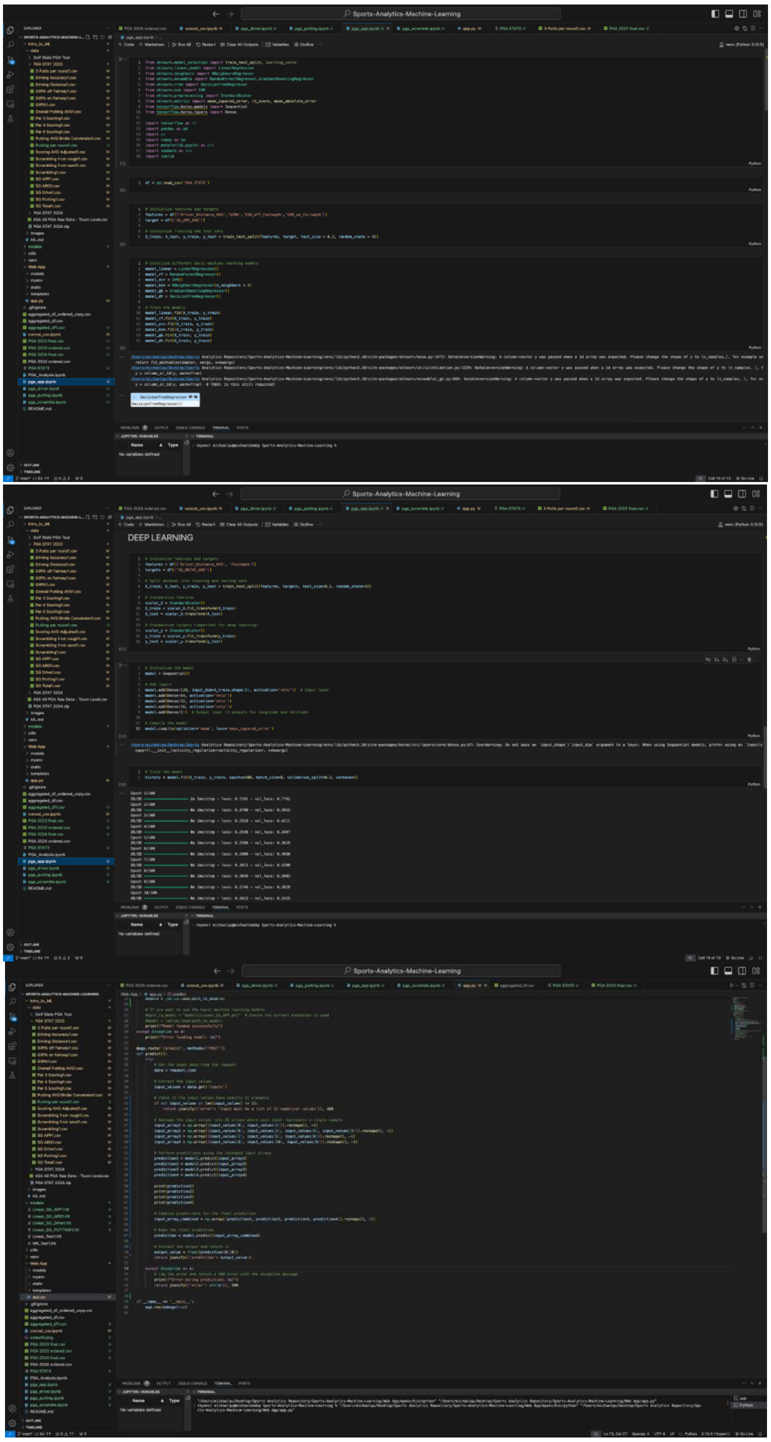


Figure 7. Screenshot of code 3

The first screenshot highlights the setup for multiple machine learning models, such as Linear Regression, Random Forest Regressor, Gradient Boosting Regressor, and Decision Tree Regressor. These models are trained on a structured dataset of PGA professional golf statistics to predict various skill-based outputs. The training dataset is split into training and testing subsets using a 20% test size. After preprocessing, each model is trained using the fit() method and

evaluated using metrics such as $R^2$ and Mean Squared Error (MSE). This section ensures the prediction accuracy by comparing performance across models to choose the most reliable one.
In this application, these models are used to predict sub-skills, such as driving accuracy, putting precision, and fairway hits, based on user-provided skill levels. The model predictions are further combined to determine the overall performance output. By leveraging multiple algorithms, this implementation improves flexibility and prediction reliability.

The second screenshot demonstrates the use of a neural network developed with Keras, focusing on a sequential deep learning model. Features like fairway distance and accuracy are standardized using a StandardScaler to enhance model performance. The deep learning model includes dense layers with ReLU activation functions, followed by an output layer configured for regression (predicting continuous values).

The model is compiled using the mean_squared_error loss function, and optimization is done via the Adam optimizer. During training, the model's performance is tracked by monitoring the validation loss, which indicates how well the model generalizes to unseen data. This deep learning approach allows the system to capture complex, non-linear relationships among features, enhancing accuracy for higher-dimensional predictions.

The final screenshot shows the backend logic built using Flask. The backend connects the machine learning models to the mobile application. Upon receiving a POST request, the backend parses input values, reshapes them for model compatibility, and runs predictions using the pre-trained models. The individual model predictions are then combined, and the final result is returned as a JSON response to the frontend.

This backend integration allows the application to communicate seamlessly between the user interface and prediction algorithms. For instance, users input their data on the app, which is sent to the backend via an API. The backend processes this data, applies the models, and returns the prediction results, which are displayed to the user in real-time.

By combining machine learning models, a deep learning framework, and a robust backend, this application achieves high accuracy and usability for predicting sports performance.

## 4. EXPERIMENT

### 4.1. Experiment 1

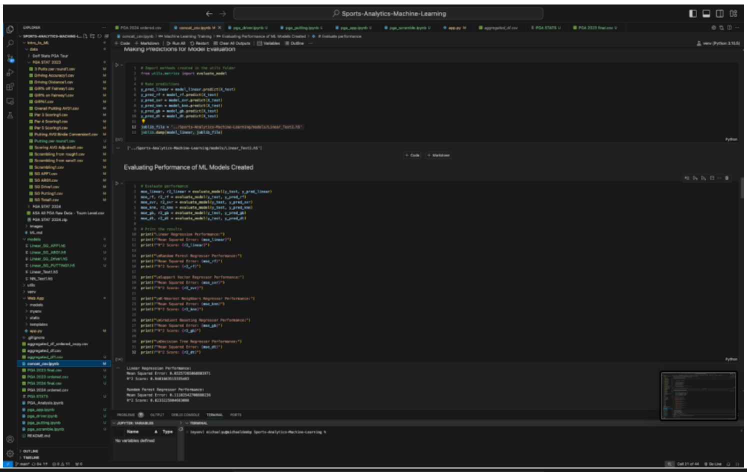
A possible blind spot in my application is the accuracy of ChatGPT’s recommendations. Ensuring high accuracy is essential for generating reliable and meaningful suggestions that effectively address users’ needs [8].

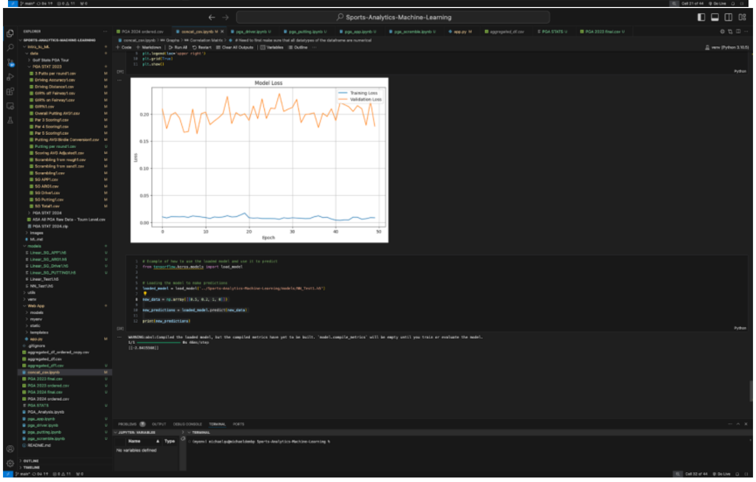
To test ChatGPT's accuracy in recommending suitable sports, an experiment will use data from professional and college athletes, including their physical and psychological attributes. This dataset will be collected from trusted sources or publicly available databases. The athletes’ information will be input into the ChatGPT system using a structured prompt. The system’s recommendations will then be compared to the actual sports these athletes pursue. The percentage of correct predictions will serve as the accuracy metric. This setup validates the program’s effectiveness by focusing on professional and collegiate athletes, as they exemplify real-world success in their chosen sports.

## 4.2. Experiment 2

Another potential blind spot in the application is the accuracy of the sports performance prediction algorithms. Ensuring accuracy is essential to provide users with reliable and actionable performance projections.

To test the accuracy of the performance prediction algorithms, an experiment will compare three different machine learning models: linear regression, neural networks, and random forests. These algorithms will be trained on the same dataset of professional and amateur athlete performances, ensuring consistency. Each model will be trained three times using different data splits, with performance evaluated based on R-squared (R^2) and Mean Squared Error (MSE). Lower MSE values and higher R^2 values will indicate better accuracy [20][21][22]. This experiment helps identify the most reliable algorithm for performance prediction, ensuring robust and accurate user-specific projections.



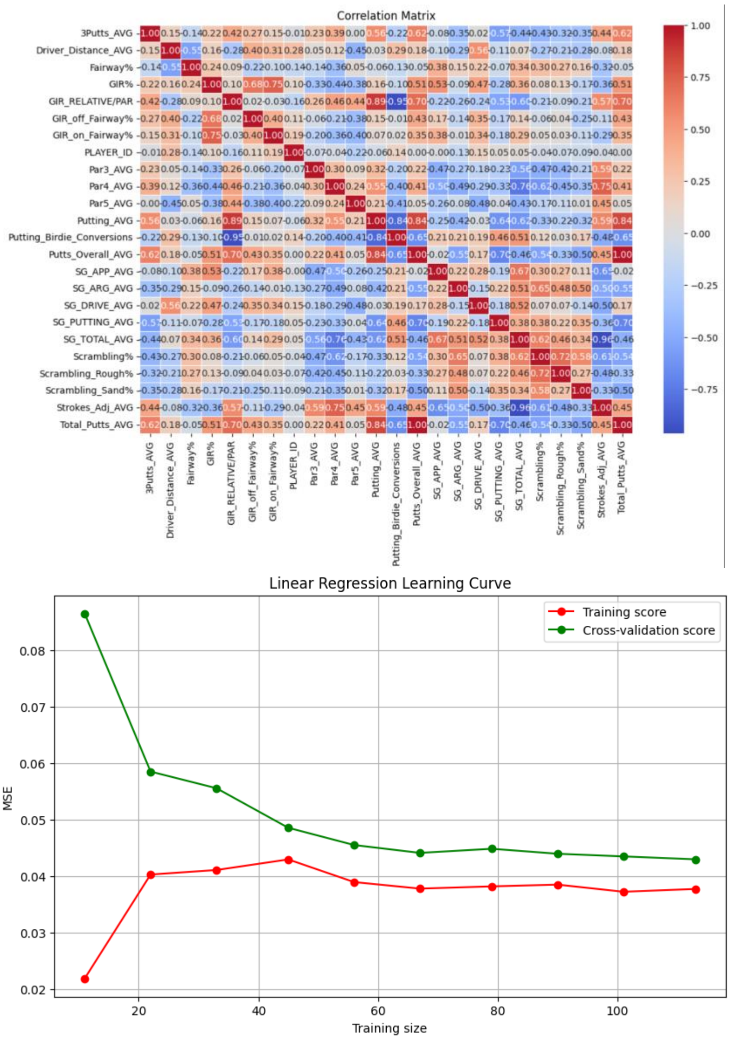



Figure 8. Figure of experiment 2

The analysis focused on evaluating the performance prediction models using metrics of Mean Squared Error (MSE) and $R^2$ scores, visualized through learning curves, correlation matrices, and loss graphs. The linear regression learning curve demonstrates the relationship between training size and error rates, with the training MSE stabilizing around 0.04 and validation scores improving slightly but plateauing. This indicates that the model generalizes decently but struggles with non-linear relationships due to its simplicity. The correlation matrix highlights the relationships between features like GIR (Greens in Regulation) and strokes gained, showing strong correlations in areas such as accuracy but weaker connections in others. This helped identify which features had the most impact on predictions and where feature engineering could improve results.

The deep learning model's loss graph shows a steady decrease in training loss, stabilizing around 0.01, with validation loss fluctuating more significantly, peaking at around 0.22. This indicates some overfitting or instability in the model's generalization. Finally, the MSE comparison chart for all models highlights that the deep learning approach achieved the lowest error at 0.01, outperforming linear regression and tree-based models like random forest and decision trees, which had higher errors ranging from 0.04 to 0.08.

Overall, the findings suggest that advanced models like deep learning better capture non-linear patterns in the data, particularly when predicting golf performance. However, the correlation matrix and loss fluctuations underscore areas where feature selection, normalization, and model tuning could further enhance accuracy and robustness.

## 5. RELATED WORK

Limited research has focused on the holistic assessment of sports suitability, with most studies emphasizing psychological aspects while neglecting physical and conditional factors 23][24][25]. One study closely aligned with this application's goals utilized a k-nearest neighbor (k-NN) algorithm to analyze 16 physical attributes to recommend sports [26]. While effective in its narrow focus, this method failed to account for more aspects, limiting its applicability. In contrast, this application integrates OpenAI's ChatGPT to analyze a broader range of factors, including physical, psychological, and environmental attributes, creating a more comprehensive and adaptable recommendation system.

Research in sports performance prediction, particularly in golf, often focuses on professional players [27][28]. One study utilized skill estimation and hole-specific features with time-weighted data and a single-layer 50-node neural network to predict scoring probabilities by hole [29]. This method demonstrated high accuracy but was limited to professional athletes and required detailed course information, restricting its generalizability. In comparison, this application uses a dual-layered approach of regression and neural networks to predict performance for amateur athletes. While less course-specific, it effectively generalizes predictions to various skill levels, ensuring its adaptability and broader applicability across different user groups.

A relevant study titled Sports Results Prediction Model Using Machine Learning explores how machine learning can predict outcomes in sports such as football with varying levels of accuracy [30]. The research uses supervised classification algorithms, including neural networks and logistic regression, to analyze match statistics and predict results like win, loss, or draw. The prediction accuracy ranged between 60% and 70%, demonstrating the potential of machine learning for sports predictions but also highlighting limitations due to domain-specific complexities and lack of external factors in the models. While effective for analyzing structured sports data, this approach has huge room for accuracy improvement. In addition, similar to other methods, its reliance on historical data limits its adaptability to unique or amateur-level scenarios. This project takes upon these ideas and further develops into other fields beside football. It partially helped to solve these limitations by integrating a holistic framework as well as huge improvement regarding prediction accuracy.

## 6. CONCLUSIONS

The application faces several limitations, primarily related to the accuracy of its systems and its further generalization of performance predictions. Since it relies on the ChatGPT API, the accuracy of recommendations depends on OpenAI's ongoing improvements, which are beyond the application's direct control. However, the prompt can be optimized further to ensure the best possible responses [31].

Another significant limitation is the generalization of performance prediction, as the current focus is primarily on golf [32]. Expanding to other sports and accommodating users across different skill levels, environments, and age groups would improve the application's inclusivity and applicability. Additionally, incorporating larger and more diverse datasets would address the system's current reliance on limited training data.

With more time, the application could enhance its adaptability by integrating sport-specific models, creating tailored experiences for a broader audience, and including real-time data collection to improve accuracy and personalization.

The potential of artificial intelligence continues to transform various fields, enabling solutions that surpass traditional algorithms. This application highlights the power of generative AI in sports analytics, offering a glimpse into its possibilities. While current limitations exist, the project demonstrates the transformative potential of AI as advancements continue to unlock new capabilities [33][34][35].

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