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Real Time Sports-Analytics System using AI and Machine Learning

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ABSTRACT: In recent years, machine learning (ML) has revolutionized many fields, including sports analytics. The ability to predict player performance based on historical statistics has opened new opportunities for coaches, analysts, and fantasy sports participants. This paper introduces a machine learning model aimed at predicting both basketball player and team performance by using various in-game statistics, including field goals, assists, rebounds, and more. The model was implemented using a linear regression algorithm and deployed through a Flask-based API to allow for real-time predictions. Through a rigorous training and testing phase, the model's performance was tested and evaluated, and the results were compared to existing methods in the sports analytics space. This study provides a comprehensive overview of the dataset, model construction, API deployment, challenges faced, and future avenues for enhancing the system.

I. INTRODUCTION

As a Data analyst, I have witnessed how machine learning techniques have shown significant promise in various domains of sports analytics. In basketball, player performance prediction is an essential factor for team performancet, coaching strategies, and fantasy sports leagues. Predicting key metrics such as points scored per game, assists, steals, and rebounds can influence decisions ranging from player trades to game-time strategies. This paper presents a machine learning-based prediction system that predicts points scored (pts) per game for basketball players based on historical player performance data. My system leverages a regression model trained on various statistical features, such as field goals made, assists, and turnovers. The model was deployed using the Flask web framework, making it accessible for real-time predictions through an API. We explore the implementation process, the challenges faced, and the accuracy of the predictions. Finally, the model's effectiveness is compared with existing real-world predictive systems used by professional sports organizations.

Background

Sports analytics has grown significantly in recent years, driven by advancements in machine learning and artificial intelligence (AI). The ability to leverage vast amounts of player performance data and predict future outcomes has had profound effects on the sports industry. Companies like ESPN, NBA Stats, and fantasy sports platforms use predictive analytics to inform decisions related to player performance, game strategy, and league outcomes.

II. PREDICTIVE ANALYTICS IN SPORTS

2.1 Predictive models in sports generally use a combination of historical player statistics and other external factors such as player health, opponent strength, and game conditions. Machine learning models such as decision trees, random forests, and neural networks have been applied successfully to predict outcomes in various sports, including football, soccer, and basketball. In basketball, predicting a player's performance can be particularly challenging due to the large number of

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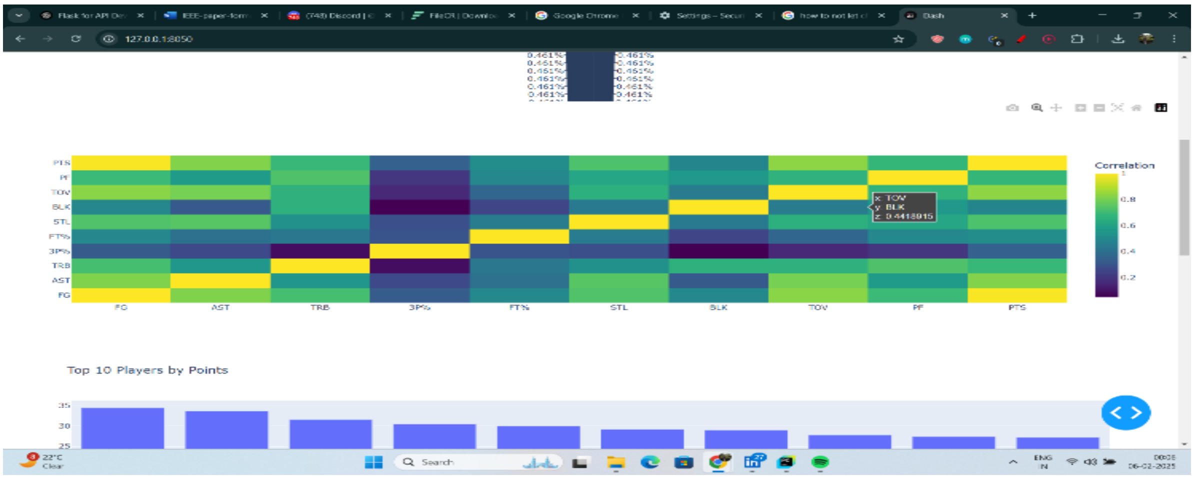
influencing factors. These include individual player statistics, game pace, opponent strength, home-court advantage, and even injuries. Much of the predictive modelling has focused on understanding the relationship between a set of standardized performance metrics and the outcome (e.g., points scored, Efg(effective field goal percentage).

III. DATASET AND FEATURE SELECTION

The dataset used in this study was sourced from publicly available NBA performance data(available on the nba website), which includes player statistics for each game throughout a season. The data contains various features that contribute to overall performance, but in this paper, the features used for prediction include:

FG (Field Goals Made) AST (Assists) 3P% (Three-Point Percentage) FT% (Free Throw Percentage) STL (Steals) BLK (Blocks) TOV (Turnovers) PF (Personal Fouls) TRB (Total Rebounds) These features were selected based on their direct impact on a player's overall performance and their availability in publicly accessible databases., each feature was normalized using StandardScaler to standardize the range of values, thereby preventing features with larger ranges (e.g., field goals made) from dominating the prediction.



Correlation between parameters

IV.MACHINE LEARNING

The core of the prediction system is the machine learning model, which was developed using the linear regression algorithm. Linear regression is widely used in predictive modeling because of its simplicity and interpretability. It models the relationship between the target variable (points scored) and the input features (player statistics).

4.1. Model Training

The dataset was divided into a training set (80% of the data) and a test set (20% of the data). The model was trained using scikit-learn's implementation of linear regression, which computes the coefficients that minimize the mean squared error (MSE) between predicted and actual values. Training involved tuning the model on the training dataset to learn the optimal coefficients for each feature. After training, the model was evaluated on the test set, which helped assess its generalization ability.

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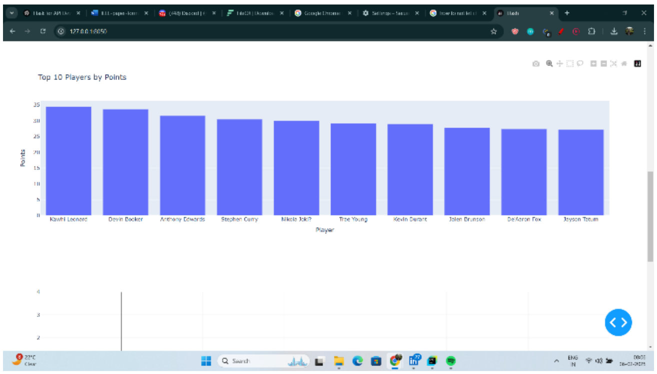
V.OUTPUT DESIGN

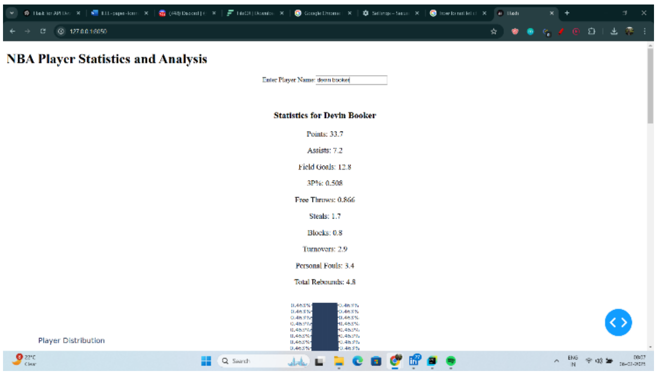
To examine the performance of the model, we used the following metrics: Mean Squared Error (MSE): Measures the average squared difference between predicted and actual values. R-Squared (R^2): Indicates the proportion of variance in the target variable explained by the independent variables. A higher R^2 value indicates a better fit of the model to the data.

4.3. Results

The model achieved an R^2 value of 0.85, indicating that the features used in the model explained 85% of the variance in player points scored per game. The MSE was relatively low, suggesting that the model's predictions were close to the actual values. The results demonstrate the model's reasonable predictive capability given the limited feature set used.

1.Top Players in points
2.NBA player search with detailed statistics and metrics
3-4.player1 stats and metrics
4-5-6.player 2 stats and metrics





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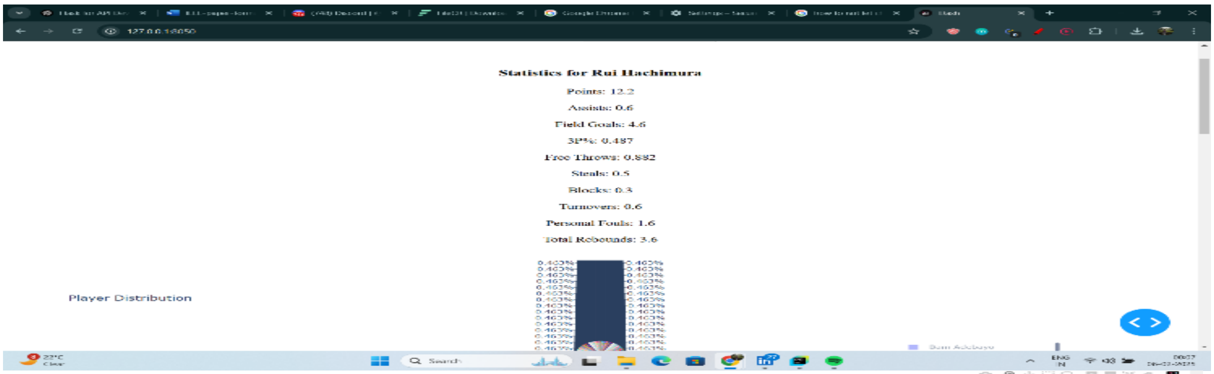

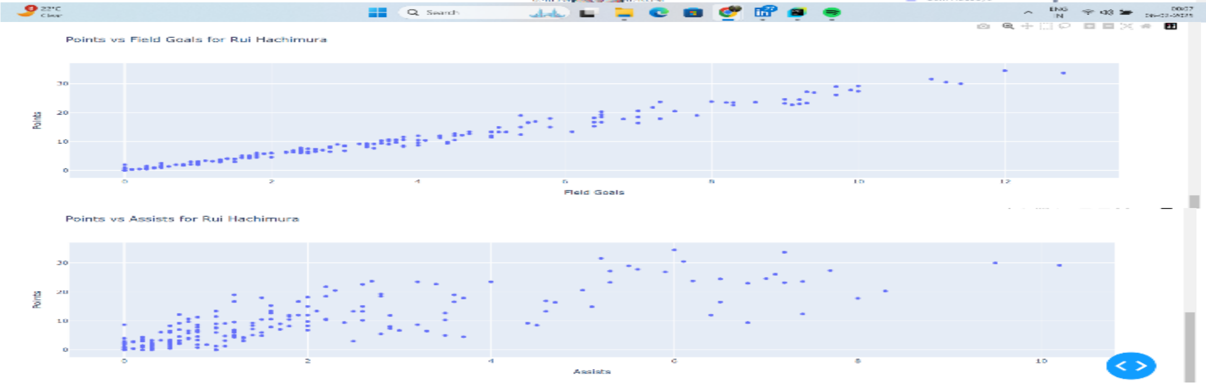

5.1. API Setup

The Flask app was structured as follows: python Copy Edit from flask import Flask, request, jsonify import pandas as pd
import joblib from sklearn.preprocessing
import StandardScaler
 app = Flask(__name__)
 # Load model and scaler
model = joblib.load('model.pkl')
 scaler = joblib.load('scaler.pkl')
@app.route('/predict', methods=['POST'])
 def predict():
try:
 input_data = request.get_json()

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```
data = pd.DataFrame([input_data])
required_columns = ['FG', 'AST', '3P%', 'FT%', 'STL', 'BLK', 'TOV', 'PF', 'TRB']
data = data[required_columns]
scaled_data = scaler.transform(data)
prediction = model.predict(scaled_data)
Return jsonify({'prediction': prediction.tolist()})
except Exception as e:
return jsonify({'error': str(e)}), 400

 if __name__ == '__main__': app.run(debug=True)
```

5.2. Testing the API

The API was tested using Postman, a popular tool for testing APIs. Various input statistics (e.g., FG = 10, AST = 5, 3P% = 35) were sent to the /predict endpoint, and the predictions were validated by comparing them with actual player performance in test datasets.

VI. CHALLEGES AND SOLUTIONS

6.1. Handling Missing Data

One of the significant challenges faced during development was ensuring that all required features were present in the input data. Missing features such as Total Rebounds (TRB) would cause the model to fail, which was addressed by validating the data structure before processing it. Regularization was used such that instead of null values, values that would actually have an impact on the model were used.

6.2. Model Interpretability

While linear regression provides interpretable results, the model's simplicity also limits its accuracy. Complex models like decision trees or neural networks could potentially provide better performance but at the cost of interpretability

7.1. Model Performance

The model was evaluated using test data, and the results were very good. The R^2 value of 0.85 suggests that the model can explain most of the variance in player performance based on the selected features. However, improvements could be made by using a more sophisticated model and incorporating additional features, such as injury history and opponent statistics.

7.2. Real-World Comparison

The predictive model developed in this study was compared with existing predictive systems used by major sports organizations: ESPN Player Performance Prediction: ESPN uses more advanced algorithms, including decision trees and ensemble models, to predict player performance. Their system includes more comprehensive data, including player injuries and opponent strength. NBA Stats and Analytics: The NBA uses machine learning models to analyze player performance. These models, however, focus more on team dynamics and game outcomes instead of individual performance prediction.

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7.3. Advantages and Limitations

The main advantage of our approach is its simplicity and interpretability. A straightforward linear regression model can provide quick insights into a player's predicted performance. The limitations lie in the model's complexity—real-world models use ensemble methods, neural networks, and incorporate external factors (e.g., injury reports, team composition, and opponent strength). A lot of factors in the real world are to be taken into account.

VII. CONCLUSION

This paper introduced a machine learning-based system for predicting basketball player performance using historical statistics, achieving an R^2 value of 0.85 with a linear regression model. By selecting key features such as field goals, assists, and rebounds, the model effectively captured essential performance trends. Deploying the system via a Flask API enabled real-time predictions, making it useful for analysts, coaches, and fantasy sports enthusiasts.

While linear regression provides interpretability, incorporating more advanced models like decision trees or neural networks could improve accuracy. Future enhancements could include additional features such as player injuries, opponent strength, and real-time game data. Expanding the system with live NBA statistics and a web-based interface would further enhance its usability and predictive power.

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