Utilizing a Hybrid CNN & Dense Network Model to Predict Team Playoff Ranking from Individual Player Regular Season Statistics

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Problem Statement

Predicting NBA playoff rankings from regular season data is non-trivial due to the high dimensionality of player statistics, variable team compositions, and the non-temporal nature of postseason outcomes.

Limitation of Prior Models:

- Traditional regression and LSTM-based time-series models assume temporal continuity and often disregard player-level granularity.
- Aggregated team statistics can obscure the influence of top-performing individuals.

Proposed Model and Contributions

Hypothesis:

Team playoff success is influenced by both individual player contributions and overall team performance. A deep learning model that integrates fine-grained player statistics and high-level team metrics can effectively predict playoff rankings for each season.

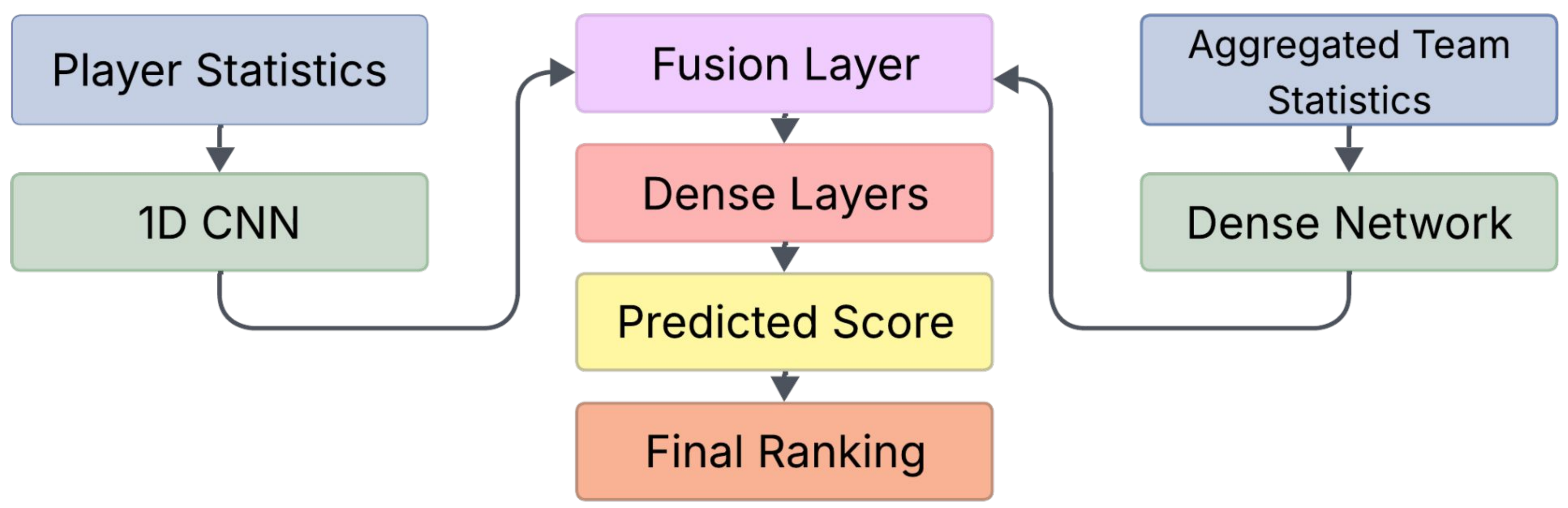
We propose a hybrid neural network with 2 parallel pathways:
- 1D CNN for player stats to capture roster patterns
- Dense network for aggregated team metrics

Their outputs are fused to predict a continuous playoff score, then ranked to produce final team standings.

Contributions:

- Hybrid Model Design
  - Combines 1D CNN for player stats and dense layers for team metrics to capture both detailed and overall performance.
- Season-Specific Training
  - Models are trained per season to avoid data leakage and reflect season-specific team dynamics.
- Top Player Influence
  - Includes top-3 player averages to emphasize the impact of star performers.
- Robust Feature Processing
  - Uses weighted averages and padding to handle missing data and varying team sizes.
- Ranking-Based Output
  - Predicts continuous scores, then converts them into playoff rankings for direct evaluation.

An Illustration of our Model



Datasets

Data:

- Datasets were retrieved from basketball-reference.com.
- Data is retrieved from seasons 2003-2024

Table: Features used from Regular Season Player Statistics 2003-2024

Purpose		Feature
Identification		Player
		Team
		Season
Performance Stats		Games played (G)
		Minutes played (MP)
	Shooting Percentages	Field goal percentage (FG%)
		3-point field goal percentage (3P%)
		Effective field goal percentage (eFG%)
		Free throw percentage (FT%)
	Box Score Statistics	Total rebounds (TRB)
		Assists (AST)
		Steals (STL)
		Blocks (BLK)
		Turnovers (TOV)
		Personal fouls (PF)
		Points (PTS)

Table: Features used from Playoff Team Statistics 2003-2024

Purpose	Feature
Identification	Team Abbreviation (Tm)
Ground truth label for training target: *Playoff_Rank*	Rank (Rk)

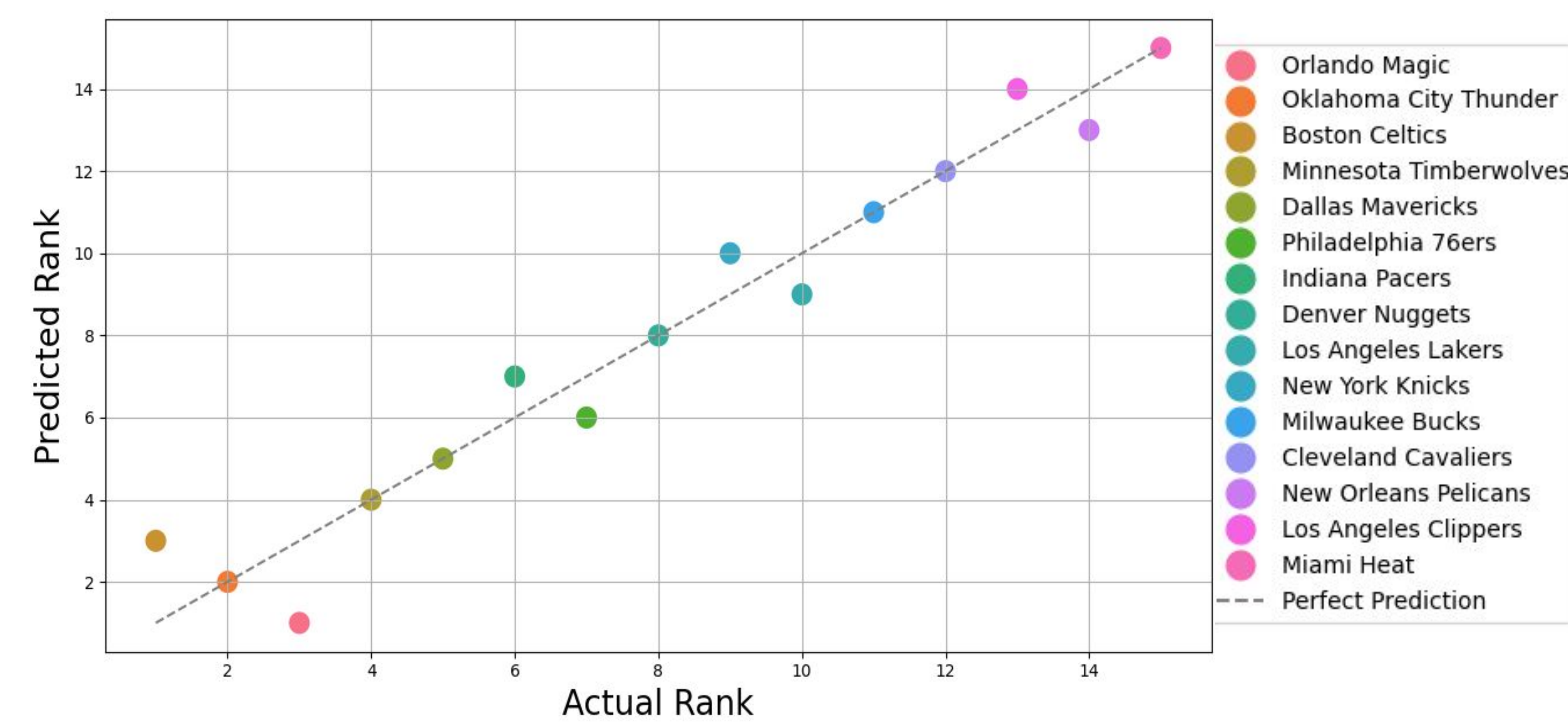
Result

Below are the overall results of our model, averaging the metrics across all seasons.

Table: Overall evaluation metrics results

Metric	Value
Spearman Correlation	0.848762
Kendall Tau	0.726152
MAE	1.511111
Perfect Matches	97
Total Teams	315

Plot of 2023-2024 Season:



As the output of our program is a ranking, non-traditional metrics are used to evaluate the model.

Table: Description of metrics used

Metric	Description	Interpretation
Spearman Correlation	Measures the rank-order correlation between predicted and actual rankings.	Values closer to 1 = better rank alignment.
Kendall's Tau	Measures ordinal association; more robust to small ranking changes.	Higher = stronger agreement in relative order.
MAE (Mean Absolute Error)	Average absolute difference between predicted and actual ranks.	Lower MAE = more accurate predictions.
Perfect Matches	Number of teams where the predicted rank exactly matches the actual rank.	Higher = more exact rank predictions.
Total Teams	Total number of teams ranked for that season.	Used for normalizing and comparing across years.

https://github.com/rayadeb/ML-Project

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