Optimizing Football Betting Strategies Using Deep Neural Networks and Modern Portfolio Theory

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Introduction

Achieving consistent profitability in football betting is challenging due to the sport's unpredictability and bookmaker edge. While Deep Neural Networks (DNNs) may offer accurate predictions on complex data, they typically neglect risk management. This research proposes and evaluates integrating DNN predictions with the Kelly Criterion (adapted from Modern Portfolio Theory) for risk-aware building of betting portfolios aiming to maximize returns over one season.

Dataset creation

We have produced a dataset of 19,168 games across the five major European leagues, combining data from three public sources: football-data.co.uk, Beat the Bookie, and Transfermarkt. The set contains game features (e.g. shots, cards), calculated metrics (e.g., xG, PPDA), and bookmaker odds. Additionally, we generated a set of 419 features from historical data, addressing the lack of available pre-match information, and utilized feature selection techniques for model training. Dataset division is presented in Figure 1.

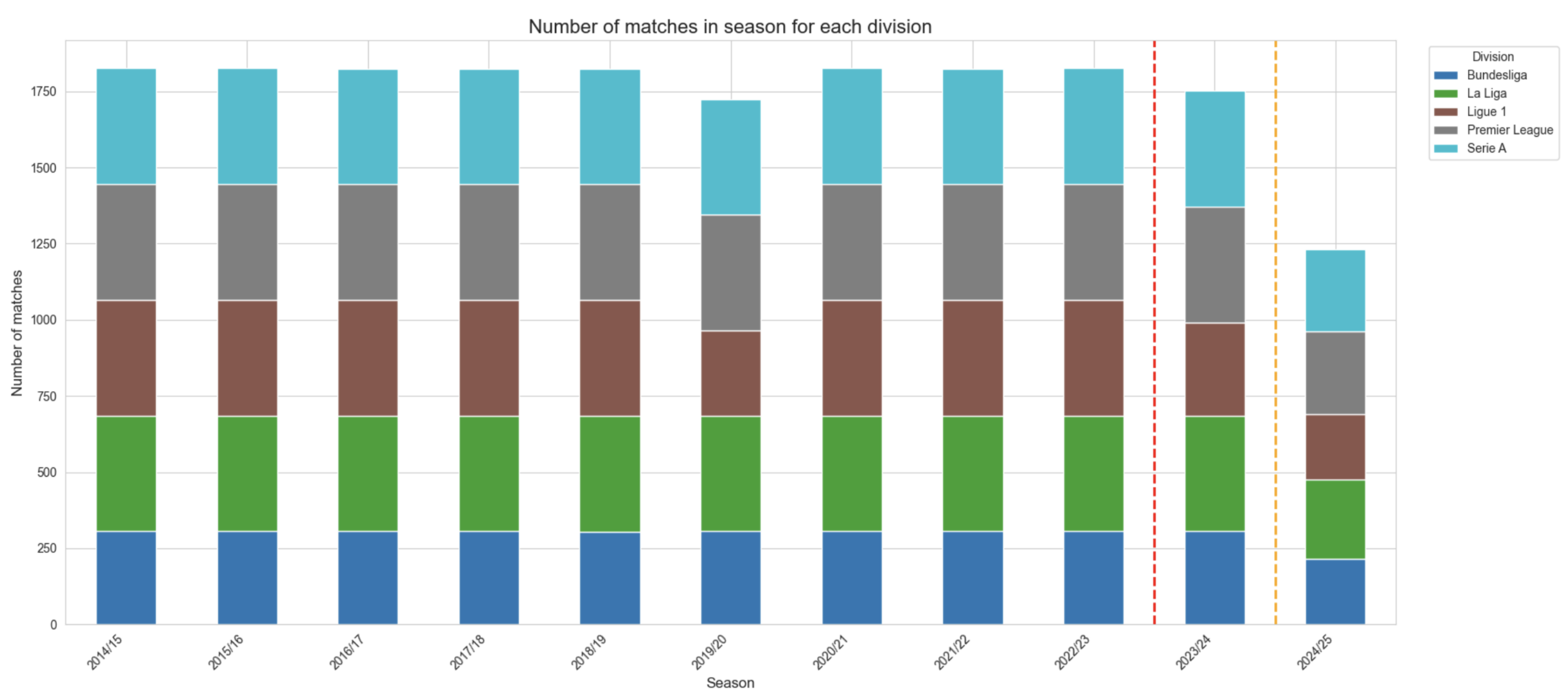

Figure 1: Data distribution between seasons, division and dataset

Model building

Six models were evaluated for predicting match outcomes (1X2): Conv1D+LSTM, Conv1D, LSTM, GRU, Feed-Forward NN, and a Soft Voting ensemble. Performance was assessed on the validation set via accuracy (prediction correctness), and cross-entropy loss (prediction confidence). Key results are presented in Table 1.

Table 1: Performance of models predicting match result

Model	Accuracy (%)	Loss
M1: Conv1D mixed with LSTM	56.16	0.9680
M2: Conv1D	55.53	0.9718
M3: LSTM	55.99	0.9666
M4: Feed-Forward NN	56.16	0.9687
M5: GRU	55.59	0.9694
M6: Soft Voting Ensemble (M1-M5)	56.28	0.9544

Betting strategies

Predicting match outcomes has proven to be insufficient. Our objective was a profitable betting strategy. To achieve this, we created functions transforming predictions into optimal bet sizes. We evaluated various functions (e.g. Kelly Criterion, threshold-based) and used a validation dataset for hyperparameter tuning. Model-function frameworks achieved validation Return On Investment (ROI) ranging from 2% to 14%. We selected the best three and used them on our test dataset.

Results

Despite promising results on the validation set, final tests showed inconsistent performance for the proposed DNN system combined with the Kelly Criterion. Only one of the three tested configurations (M3+Kelly) achieved a positive ROI of 3.35%.

M3+Kelly performed better than a simple strategy of always betting on the home team (-13.93% ROI), and some standard machine learning models like Random Forest (2.35%) and K Nearest Neighbours (-3.07%). However, it achieved a slightly worse result than the Gradient Boosting Classifier model (4.00% ROI). The poor results of the other DNN models compared to simpler methods, along with discrepancies between seasons, suggest that achieving stable profits is challenging, potentially due to shifts in game dynamics between seasons or model overfitting.

Conclusion

This research explored combining DNNs and the Kelly Criterion for managing risk when building football betting strategies. Despite promising validation, test performance was inconsistent; of all DNN models only the LSTM+Kelly model produced a profit. Football's unpredictability and model generalization issues make stable profitability challenging, necessitating further refinement.