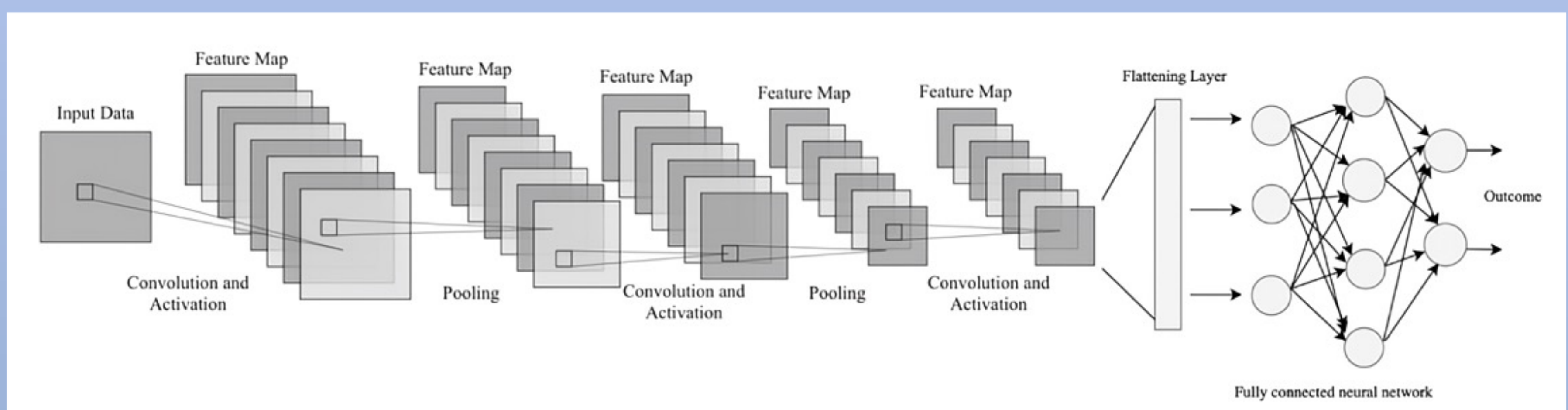
FOOTBALLNET: a Deep LEARNING NETWORK for FOOTBALL COMPETITION PREDICTION

Tongfeng Wang[a], Jing Wang[b]*
[a] University of Southampton, School of Arts and Media Technology, tw1m24@soton.ac.uk
[b] Capital university of physical education and sports, School of Sports Journalism, wangjing@cupes.edu.cn*

Introduction

With the advancement of technology, artificial intelligence (AI) and big data have significantly impacted sports communication, particularly in enhancing audience engagement, personalized content recommendations, real-time data analysis, and targeted advertising. This study explores the novel application of convolutional neural networks (CNNs) for predicting sports event outcomes. Leveraging CNNs' ability to identify intricate patterns, the proposed method shows improved accuracy, precision, recall and F1 score compared to six traditional models, achieving up to 93%- 97%, 87.8%-92.2%, 91.5%-96.5% and 90.7-92.9 respectively. Besides, while there are some fluctuations influenced by Gaussian noise, the four targets of our model are still much higher than other traditional models, and both could show the stability and reliability of the model. The result of this finally indicates that CNN offers a promising method for enhancing sports analytics and permits reliable and accurate predictions of complicated datasets.

Methods

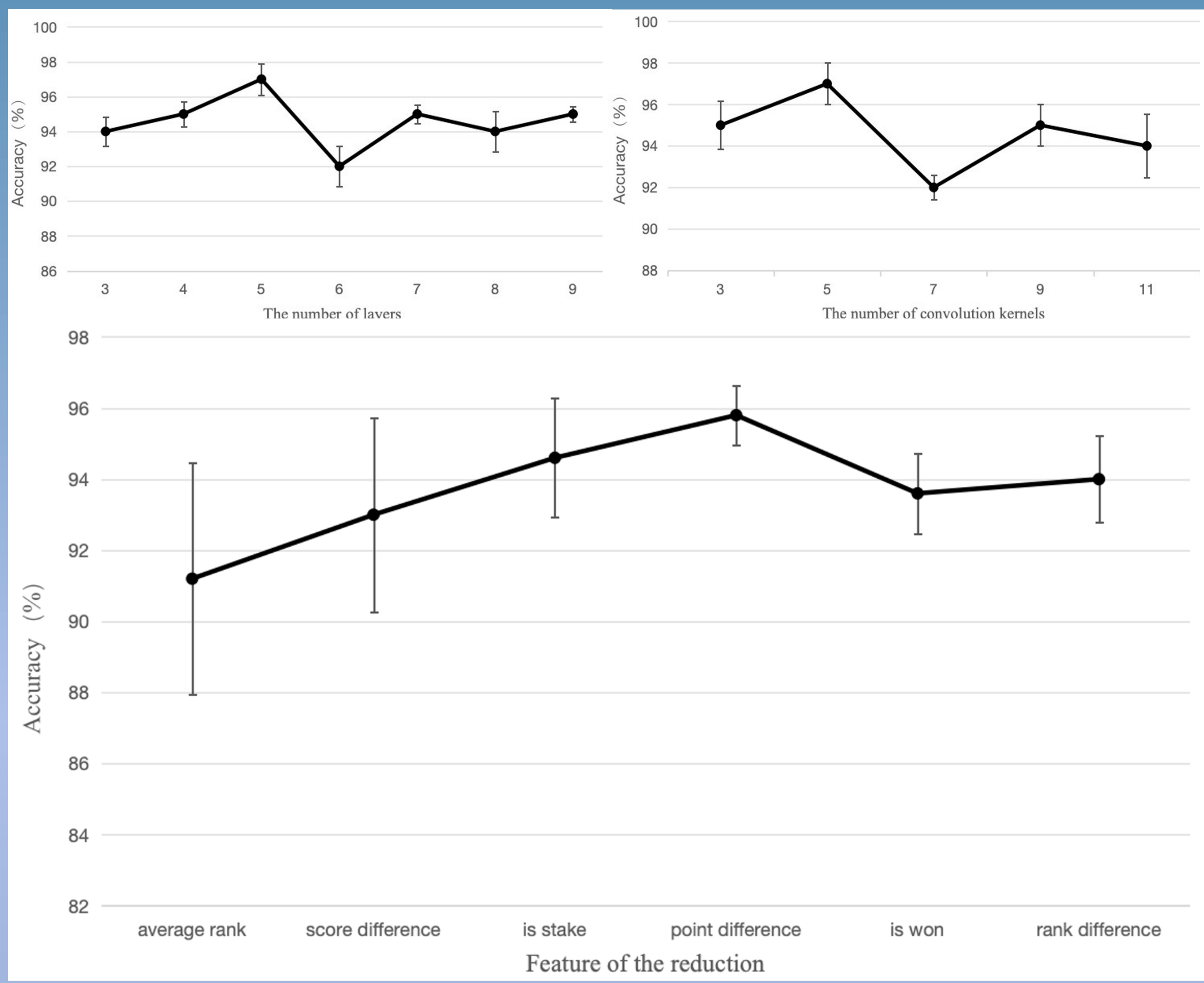


The CNN extracts features through three 1D convolutional layers designed to capture hierarchical patterns. The first layer (conv1) uses 16 filters to detect local features, followed by conv2 with 32 filters for more complex patterns, and conv3 with 64 filters for feature refinement. Each layer maintains input size using a stride and padding of 1, with ReLU activation adding non-linearity to enhance learning. Max-pooling, applied after each convolutional layer with a kernel size and stride of 2, reduces dimensionality, extracts key features, and prevents overfitting. After feature extraction, the model transitions to a fully connected network. The flattened feature maps pass through fc1, a layer with 64 neurons and ReLU activation, while dropout with a 0.5 probability helps avoid overfitting by deactivating random neurons. The final layer (fc2) has two neurons with sigmoid activation to output probabilities for binary classification. By integrating convolutional, pooling, and fully connected layers, this architecture efficiently extracts features and performs classification, making it highly suitable for sequence data analysis.

Results

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Original data	95±2.0	90±2.2	94±2.5	91.8±1.1
Noisy data	90.7±1.7	88.7±1.9	91.4±2.6	90.4±2.2

	Logistic Regression	Decision Tree	Random Forest	SVM	XGBoost	MLP	CNN
Accuracy (%)	68.8±5.1	59.9±2.3	63.5±3.2	69.1±2.6	66.5±3.3	66.1±2.2	95±2.0
Precision (%)	67.2±5.6	57.5±2.9	61.2±3.9	67.8±2.7	64.7±3.5	65.1±6.5	90±2.2
Recall (%)	66.3±4.9	58.1±2.2	62.1±3.5	65.9±1.9	64.0±3.2	65.7±15.7	94±2.5
F1 score	66.7±0	57.8±1.5	61.7±2.9	66.8±2.5	64.4±3.0	63.9±6.6	91.8±1.1



The CNN model exhibits exceptional robustness, achieving significantly higher accuracy, precision, recall, and F-score compared to traditional models such as Logistic Regression, Decision Tree, and SVM, even when subjected to Gaussian noise, demonstrating its reliability. Feature selection plays a pivotal role in improving performance; critical features like "is won" and "point difference" enhance stability, while removing less impactful features like "is stake" reduces noise and improves accuracy. The number of convolution kernels is carefully moderated, with performance peaking at 5 kernels, as adding more leads to overfitting and diminished generalization. The model achieves optimal results with 5 layers, balancing complexity and overfitting through regularization techniques. This architecture effectively integrates robustness, precision, and efficiency, making it ideal for high-performance prediction tasks.

Conclusion

The CNN achieves 95% accuracy, 90% precision, 94% recall, and a 91.8 F1 score, outperforming other models in capturing intrinsic patterns in sports data with minimal feature engineering. Changes in convolutional layers or kernels have little effect on accuracy, which remains around 95%. Retaining features like "is won" and "point difference" stabilizes the model, while removing "is stake" improves performance. After Gaussian noise experiments, performance metrics show slight fluctuations but remain around 90%, highlighting CNN's robustness with high-dimensional sports data. This research demonstrates CNNs' potential for sports outcome forecasting and encourages further exploration, including hybrid models and domain-specific refinements.