FOOTBALLNET: a Deep LEARNING NETWORK for FOOTBALL COMPETITION PREDICTION

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Abstract—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. Predicting sports outcomes remains a challenging task due to the inherent unpredictability of factors such as player performance, weather, and tactical decisions. Traditional statistical models and machine learning algorithms, like logistic regression and XGBoost, have had limited success in capturing complex patterns in high-dimensional data. 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.

CCS CONCEPTS: Machine learning, Artificial intelligence

Additional Keywords and Phrases—AI, football predictions, convolutional neural networking, game analyze

1 INTRODUCTION

With technology still finding its way into every field of life, AI and big data are completely changing the face of sports communication. Such innovations do increase audience interaction by providing an experience that is much more engaging and participatory in nature, while personalized content recommendation algorithms ensure that fans get all information tailored to their favorite teams or players. Real-time data analysis makes for more informative live commentary and decision-making, while targeted advertising ensures that brands reach their respective target audiences. All in all, AI and big data are changing how sports are consumed and experienced by fans and other stakeholders alike **Error! Reference source not found.**. Predicting the outcomes of games in the fast-paced, often-unpredictive world of sports is both an extremely challenging task and engrossing with anticipation. Accurate predictions may be useful for various parties, ranging from fans and analysts to team management and sport betting companies [2]. However, forecasting sports is very difficult since their outcome is inherently uncertain and depends on many sectors of player weather conditions, spectator influences, home team advantage, the underdog wins and so on [3]. The capture speed with traditional statistical and analyzed models is pretty slow, with lower reliability in the predictions.

Current approaches to predict the outcome of a match are mainly statistical methods[4], machine learning algorithms including logistic regression, random forests, and XGBoost[5]. While these techniques have seen success in a few specific applications, they often require significant feature engineering and may struggle to uncover patterns in high-dimensional data. Recently, deep learning methods have attracted attention because they can be supremely good at processing and analyzing complex visual data[6]. However, their applications in predicting sports event outcomes are at the rudimentary stage of development, with ample scope for exploration and refinement.

FootballNet: A Novel Application of Convolutional Neural Networks for Sports Outcome Prediction. By this approach, based on the power of CNNs to detect intricate patterns and correlations inside complex datasets, [7]the prediction can considerably be improved and outperforming traditional models. Preliminary results demonstrate our FootballNet outperforms other existing models by a fair margin in terms of accuracy[8]. Especially in comparison with six models for instance, logistic regression, XGBoost, MLP, random forest, SVM and Decision tree, the accuracy of the FootballNet reaches 97%, while altering the amount of convolutional layers and the number of convolutional kernels has little effect on the final accuracy, which is maintained at around 95%. This would highlight the potential to bring transformative advancements to the field of sports analytics. By utilizing this deep learning technique, future prediction models will be able to handle more complex, multi-dimensional data, providing more precise and reliable support for sports outcome forecasting, and driving the field into a new era of intelligent analytics.

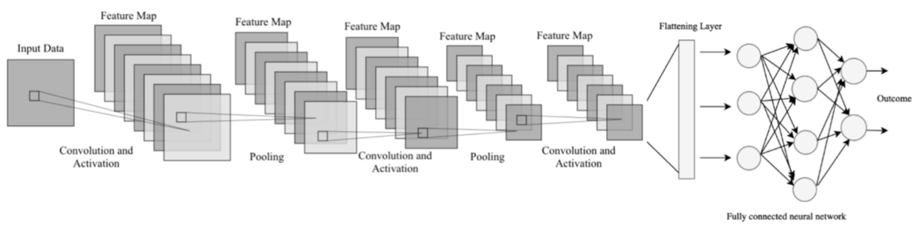

Figure 1: The simplified topology of footballnet convolutional neural network

2 THE DATASET AND FEATURE

Nowadays, the data of football games has become a crucial part of modern sports analytics, which would be used by football teams (including the home team and the away team), analysts, media and so on for insight into the performance of players and teams, in order to generate strategy and draw a corresponding conclusion. And the football data not only includes some familiar nouns like goals, possession, shots, offside and foul typically, but also some advanced metrics, which comprised Expected goals (XG), Expected Assists (EA), Expected Goals Against (XGA), Pass Accuracy, Tackling Success Rate and the like. Besides, the method of data collection also has a revolution from recording by skilled and professional analysts to sophisticated automated systems using supercomputers, wearable devices and optical tracking systems. These evolutions have significantly increased the volume and the accuracy of data for analysis more available. There are several companies like Opta Sports, GeniousSports and Wyscout [9] that specialize in collecting and distributing the football games' data, catering for different purposes within the football field. This kind of data is used to analyze team performance, predict game outcomes, inform betting, and increase the engagement of fans.

In this study, we chose six factors as features, they are ranking difference, average rank, point difference, score difference, is won and is stake. And all the data is coming from three datasets: the dataset of FIFA soccer rankings from 1993 to 2018 which courtesy of Tadhg Fitzgerald, this dataset contains all available FIFA men's international soccer rankings from August 1993 to April 2018. The rankings and points have been scraped from the official FIFA website. Includes all ~200 teams and available data from 1993-2018, which includes Rank, Country, Country Abbreviation, Total Points, Previous Points, Rank Change, Average Previous Years Points, Average Previous Years Points Weighted (50%), Average 2 Years Ago Points, Average 2 Years Ago Points Weighted (30%), Average 3 Years Ago Points, Average 3 Years Ago Points Weighted (20%). The second dataset is International football results from 1872 to 2024 which courtesy of Mart Jürisoo, this dataset is gathered from several sources including but not limited to Wikipedia, rsssf.com, and individual football associations' websites, which includes 47,777 results of international football matches starting from the very first official match in 1872 up to 2024. The matches range from FIFA World Cup to FIFI Wild Cup to regular friendly matches. The matches are strictly men's full internationals, and the data does not include Olympic Games or matches where at least one of the teams was the nation's B-team, U-23 or a league select team. and the final dataset is FIFA World Cup 2018 dataset which courtesy of Nuggs, this dataset contains 32 participating teams, each team will have 3 matches in the group stage, so each match is mentioned vs whom, the history between those 2 teams with wins minus losses. The match's history is up to 2012-2014. So, there is a couple of years missing here, and the FIFA rank is up to date, which will be updated every month.

In addition, here we would like to explain the basics of these six features. We read the data from the "FIFA soccer rankings from 1993 to 2018" database and store it in a DataFrame called "rankings" and then select specific columns from it: "rank", "current year average weighted", "two years ago weighted" and "three years ago weight". Read the data from the "International football results from 1872 to 2024" database and store it in a DataFrame named "matches", then select specific columns: "home score" and "away score". First is "rank difference", we use "rank home" minus "rank away"; the second is "average rank", where we add "rank home" and "rank away" and divide the result by two; The third one is "point difference", firstly, we add "current year average weighted", "two years ago weighted" and "three years ago weight" to get the weighted points for each team and store them in a new table called "weighted point", the "point difference" is obtained by subtracting "weighted point home" from "weighted point away"; the fourth is "score difference", which is calculated by subtracting the away score from the home score; the fifth one is "is won", we need to judge whether "score difference" is greater than 0, in order to judge whether the result of the match is a win or not.

The last one is "is stake", which is a bit more complicated, we need to define a list of "average rank", "rank difference" and "point different", and then create a Boolean array, in which the element in the wrongs is True, which means that the model made a wrong prediction in the test set, i.e. the actual result is different from the model. We then plot the Kernel Density Estimates (KDE) of the feature values in all the samples, i.e., we plot the probability density curves of the features in the overall samples, and then we compute and print out the distribution of the betting features in the incorrectly predicted samples and its proportion in the total number of incorrectly predicted samples. Then we compute and print out the distribution of the betting features in the overall samples and its proportion in the total number of incorrectly predicted samples.

3 CONVOLUTIONAL NEURAL NETWORKING

3.1 Fully Connected Neural Network

The Fully Connected Neural Network (FCNN) is a category of artificial neural network where each neuron in one layer and every neuron in the next is highly connected. It includes an input layer, one or more hidden layers, and an output layer [10]. Each neuron applies a weighted sum of inputs followed by an activation function to introduce non-linearity. FCNNs are trained using backpropagation and optimization algorithms to minimize prediction error. While effective for smaller datasets, FCNNs become less efficient with large inputs like images, where architectures like Convolutional Neural Networks are preferred. FCNNs are widely used for classification and regression tasks.

3.2 Convolutional Neural Networking

The convolutional neural network is a specialized type of neural network primarily used for tasks involving pattern recognition, especially in image analysis [11]. This section outlines the CNN architecture, highlighting its core components based on the model implemented in the provided code.

3.2.1 Convolutional Layer

The CNN performs feature extraction from the input data through convolutional layers. Here, three 1D convolutional layers are defined for the model: The first 1D convolutional layer, called conv1, applies 16 filters of a kernel size of 3 to capture local features from the input sequence. The subsequent layer, conv2, enhances the previous layer with 32 filters to capture more complex patterns. The third layer, conv3, is also convolutional, with 64 filters; it is intended to further refine the features extracted so far.

Each convolutional layer uses a step of 1 and padding of 1 so that, after the convolution, the input size is maintained. To add some kind of non-linearity-representing possible intricate patterns-the model might want to capture; ReLU is an activation used here.

3.2.2 Pooling Layer

After each convolutional layer, a max-pooling operation is applied for the down-sampling of the feature maps. The MaxPool 1D layer with kernel size and stride of 2 is used in the model. This layer reduces dimensionality and, thus, optimizes computational efficiency while retaining important features. Pooling summarizes some of the features going through the convolution layers, reducing the risk of overfitting.

3.2.3 Fully Connected Layer and Dropout

The model contains a fully connected convolution and pooling. After flattening the pooled feature maps, the data would pass through two fully connected layers: The first fully connected layer fc1 would contain 64 neurons, with ReLU activation. To avoid overfitting, dropout is applied with a probability of 0.5 that deactivates random neurons for training. fc2 is the fully connected layer that consists of 2 output neurons. Then, this forms the final prediction with the sigmoid activation to generate probabilities on a binary classification.

3.2.4 Topology

The CNN architecture in this model incorporates an input layer, three convolutional and pooling layers, followed by a fully connected network. The convolutional layers capture hierarchical features of the input, while the pooling layers reduce dimensionality. Finally, the fully connected layers map the extracted features to the output prediction. The overall architecture efficiently combines feature extraction and classification, making it suitable for sequence data analysis, as implemented in the model.

4 TESTING AND RESULTS

The Table 1 records a comparative analysis of a couple of machine learning models in aspects of accuracy, precision, recall, and F1 score, and the model includes Logistic Regression, Decision Tree, Random Forest, SVM, XGBoost, MLP, and CNN. Overall, the CNN model makes the best performance, with an accuracy of around 95%, the proportion of precision and recall is near 90% and 94% respectively, and an F1 score of 91.8% approximately, which is much better than the other models. This could indicate that CNN makes a good job in capturing complex patterns in the data and achieves a harmonious balance in classifying between positive and negative samples. In contrast, the competitiveness shown of traditional machine learning models like Logistic Regression, Decision Tree, and Random Forests not strong. Especially, the performance in accuracy and precision of Decision Tree, with only 59.9% and 57.5%, this leads to the limitation in handling complex decision boundaries.

In terms of standard deviation, CNN is not only doing an excellent performance in metrics, but also showing the high stability, which could illustrate the ability of consistency in different datasets or experiments. This stability plays an instrumental role in machine learning models because this means it deserves to be trusted in practical applications. In comparison, MLP has shown a large number of deviations in recall percentage (±15.7), which would suggest this model lacks stability and sensitivity to data variations.

Predicting football match outcomes is quite challenge because of the limited availability of informative data. Consequently, incorporating football-specific knowledge, expert insights, and effective data engineering is crucial for developing accurate predictive models. Additionally, selecting the right methodologies and algorithms—whether from statistical models, machine learning, or rating systems—plays a key role in enhancing prediction accuracy [12].

Table 1: The comparative analysis results of the proposed model against existing models in term of accuracy percentage, Precision percentage, Recall percentage and F1 Score.

	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

4.1 Ablation Study

4.1.1 Model layer

The Figure 2 shows that the number of model layers has a noticeable impact on accuracy. While increasing the number of layers does not always result in higher accuracy, the model reaches its peak performance at five layers, with an accuracy prime to 97%. Even with fluctuations at other layer counts, the accuracy consistently stays above 90%, and despite variations, it remains around 95%, which is quite impressive. As part of this process, we conducted a neural architecture search (NAS), exploring different layer configurations.

After evaluating the results, we selected the five-layer model as the final network structure, as it provided the highest accuracy and balanced performance. Overall, the model performs well across different layer configurations, and the accuracy rate of 95% is already sufficient for many practical applications.

In order to find the best performance of layers for our model, which needs to be tested on both training and validation datasets. Further, we gained the accuracy on the test set, finding that the 5th layer made the best performance. In the Tootballnet model, regularisation and other methods have been used to keep a balance between overfitting and model complexity [13].

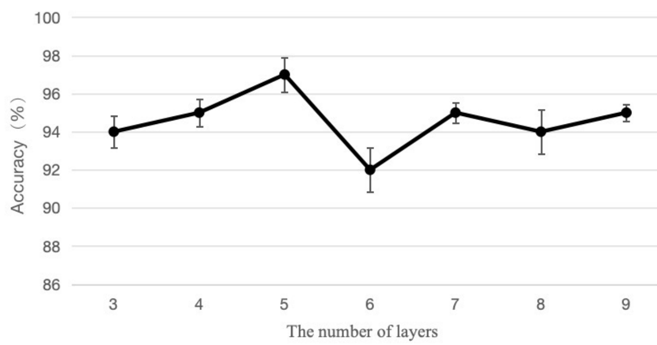

Figure 2: Impact of model layers on accuracy

4.1.2 Number of model convolution kernels

The Figure 3 illustrates the effect of varying the number of convolution kernels on model accuracy. When the figure of convolution kernels is limited to 3, the model achieves an accuracy of approximately 95%. As the amount of kernels augment to 5, there is a notable improvement in accuracy, which reaches a maximum of 97%. That means that, within a specific range, raising the number of convolution kernels first improves the capability of catching relevant features of the model and therefore improves performance [14]. The peak at 5 kernels indicates an optimal balance in this particular setting between model complexity and accuracy. Going beyond 5 convolution kernels, accuracy degrades starting with increased kernel counts of 7, 9, and 11, with the saturating performance of the model at approximately 95%.

This tends to indicate the law of diminishing returns, where adding further kernels provide no further improvements in accuracy, possibly even degrading it. The reason for this may be overfitting or a higher model capacity that does not generalize well on unseen data. While the model is effective with increased moderation in terms of convolution kernels, too much complexity can nullify overall model effectiveness [15].

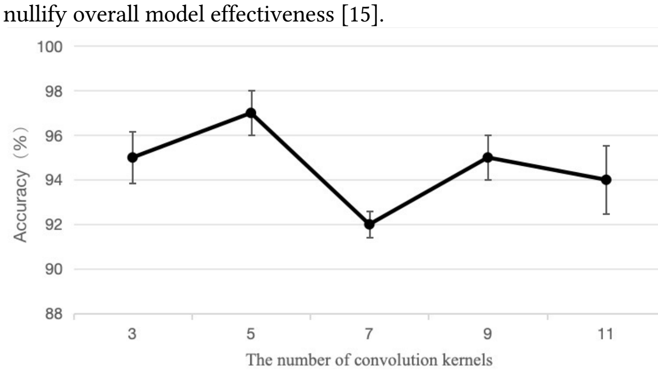

Figure 3: Influence of the number of model convolutional kernels on accuracy

4.1.3 Reduced features

The figure 4 offers a detailed view of the impact on removing a single feature on model accuracy, with each data point has represented the accuracy level after the cutting a specific feature, accompanied by error bars indicating the range of variability. If we look at the examination of each feature removal has revealed special effects on model performance carefully, suggesting differential roles that each feature plays in the model accuracy.

Let’s start with the “average rank” feature, the result in an accuracy of approximately 90% when it is removed, though there is quite a big error margin. This wide margin of error indicates there is a considerable uncertainty in the model’s respond [16], which also suggests “average rank” might include some useless or redundant information, and these kinds of information can not make a consistent contribution to accuracy. However, the large error range also means uncertainty regarding its exact impact, which might because of its mixed influence on certain data subsets within the model.

Let’s move on to the “score difference” feature, we see an increase to around 92% about accuracy when this feature has been cut. Although there is a moderate improvement in performance, the corresponding error bars are still comparatively broad. This would suggest that while “score difference” might make some interference to the model, leading to improved accuracy when it has been excluded, there are different effects in different instances, which would indicate an unstable contribution to model performance. The remaining uncertainty shown by the error bars indicates that “score difference” is partially influential but not entirely beneficial for predictive accuracy [17].

The third removal feature is “is stake”, when it is removed, the highest accuracy would be observed in the model, reaching approximately 96%. Besides in this case the error margin is also moderate, this suggests that “is stake” consistently reduces the Footballnet model accuracy when included. This result indicates that “is stake” likely brings some irrelevant information and excluding it could lead to a significant increase in model performance. If we compare the relatively narrower error range with the previous features, the detrimental impact of “is stake” is consistent across data subsets, marking it become a feature which would have some negative effects during the model’s prediction.

After talking about the feature “is stake”, the next part is that excluding the “point difference” feature, which could lead to the accuracy slightly declining to around 94%, and at the same time there is a significant reduction about the variability, this indicated by narrower error bars. This suggests that “point difference” plays a quite stable role in the Footballnet model, and its exclusion, although it would cause a marginal decrease in accuracy, does not take significant inconsistency. This pattern indicates that “point difference” is a suitably beneficial feature, adding stability to the model without over-fluctuating contributions to accuracy.

For the “is won” feature, the outcome of accuracy when it has been removed is just below 94%. The narrow error range here shows that this feature could make a consistent contribution in order to improve model performance. There is a slight reduction in accuracy after removing “is won” and this has confirmed its positive role, because it seems like in the model appears to be beneficial, and makes it become a valuable feature that would enhance predictive accuracy stably. Keeping this feature is likely useful and positive, because it contributes to the reliability of model prediction without substantial fluctuations [18].

Finally, after the exclusion of the “rank difference” feature, the accuracy number stabilizes at approximately 93%, with an acceptable error range. There is a quite stable accuracy amount after the “rank difference” has been removed, this suggests that “rank difference” makes a stable, with not highly influential impact on the model. Excluding the feature “rank difference” neither significantly increases nor decreases the accuracy, which indicates that this feature is relatively neutral in terms of predictive ability. However, its moderate error margin indicates that while it does not introduce substantial noise, it also does not make a significant enhancement on accuracy, so there is a limited influence of Footballnet model performance with this feature.

In conclusion, keeping the feature like “is won” and “point difference” (in some cases) would help to make the accuracy more stabilized while removing the feature such as “is stake” would enhance the performance by reducing noise [19]. Therefore, feature selection based on detailed analysis can help to build up a model that might include both high accuracy and consistency two advantages, and this also highlights the importance of understanding each feature’s role in the model’s prediction mission.

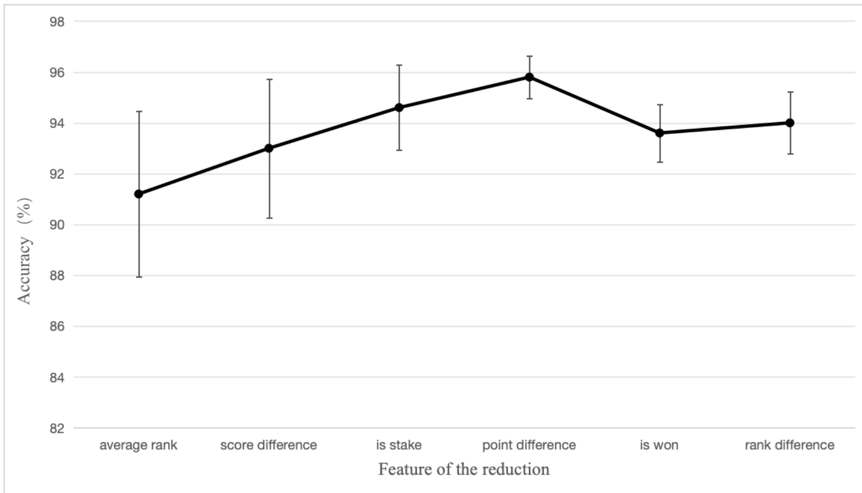

Figure 4: Influence of reducing different feature on accuracy

4.1.4 Robustness

The Table 2 has compared the difference between original data and noisy data in accuracy, precision, recall, and F1 score. If we talk about the original data, accuracy is around 95%, while the percentage of noisy data decreases to nearly 90.7%, which could indicate there is a drop in the Footballnet model's accuracy because of the noise. The proportion of precision also drops from 90% to 88.7% approximately, this has suggested there is an increase in false positives when the model is operating the noisy data. This change illustrates that there would be more errors made by this model when identifying positive samples in the noisy conditions. As a result, the ability of accurately distinguish between classes would reduce.

On the other hand, the decrease in the percentage of recall and F1 score further illustrated that the noise plays a negative role in the Footballnet model's performance. The recall for original data is almost 94%, but at the same time, noisy data has fallen to 92.4% approximately, which could indicate that the number of positive samples has increased that are misclassified as negative because of the noise. The F1 score decreases from near 91.8% to around 90.4%, both precision and recall could show that they are affected by the noise. Overall, these results could highlight the importance of reducing noise in data preprocessing and modelling [20], although it is true that there are some fluctuations of our Footballnet model after the Gaussian noise experiment, its accuracy, precision, recall and F-score are still much higher than other traditional models, which could reflect the stability and reliability of our model.

Table 2: The comparative analysis results of original data and noisy data in term of accuracy percentage, Precision percentage, Recall percentage and F1 Score.

	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

5 CONCLUSION AND FUTURE WORK

This work is going to demonstrate the excellent capability of convolutional neural networks in predicting football game outcomes, further improving conventional machine learning models like logistic regression, XGBoost, and random forests.

The accuracy of about 95%, the precision of about 90%, the recall of about 94% and the F1 score of about 91.8, have proved that CNNs were much better at modelling the intrinsic pattern in sports data with little feature engineering compared to the other models. Second, it is evident from the research that a change in the number of convolutional layers and kernels does not really affect the overall accuracy, which stays around 95%, and keeping the feature "is won" and "point difference" might make the model more stabilized, removing the feature "is stake" might enhance the model's performance. After the experiment of Gaussian noise, the four targets have a slight fluctuation, but all of them is around 90. This indeed reflects the robustness and reliability of CNNs in dealing with complex, high-dimensional data related to sports analytics. This research opens perspectives for further exploration in the domain of sports outcome forecasting using deep learning techniques. Further refinements in CNN architectures could be envisaged in further works by incorporating domain knowledge or proposing hybrid models to improve the reliability of predictions. Besides, scalability to other sports and types of data is an aspect that will be of interest for studying in greater detail. It is an exciting opportunity, indeed, to apply AI and big data in sports media and beyond.

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