Fútbol Smart Coach: Analyzing Corner Kicks using Computer Vision

Abstract—In this paper, we utilize computer vision to develop a tool for youth coaches to formulate set-piece tactics for their players. We used the Soccernet database to extract the ResNet features and camera calibration data for over 3000 corner kick across 500 professional matches in the top 6 European leagues (English Premier League, UEFA Champions League, Ligue 1, La Liga, Serie A, Bundesliga). Leveraging the provided homography matrix, we construct a feature vector representing the formation of players on these corner kicks. Additionally, labeling the videos manually, we obtained the pass-trajectory of each of the 3000+ corner kicks by segmenting the field into four zones. Next, after determining the localization of the players and ball, we used event data to give the corner kicks a rating on a 1-4 scale. By employing a Convolutional Neural Network, our model managed to predict the success of a corner kick given the formations of players. This suggests that with the right formations, teams can optimize the way they approach corner kicks. By understanding this, we can help coaches formulate set-piece tactics for their own teams in order to maximize the success of their play. The proposed model can be easily extended; our method could be applied to even more game situations, from free kicks to counterattacks. This research project also gives insight into the myriad of possibilities that artificial intelligence possesses in transforming the domain of sports.

Keywords—soccer, corner kicks, AI, computer vision

I. Introduction

THIS 3.5 billion supporters around the world, no sport connects people together better than soccer. [11] Billions tune in to watch their favorite teams and players compete at professional levels, while hundreds of millions play at a recreational or amateur level. [14] Tens of millions of youth athletes dedicate hundreds of hours to the sport annually.

Each soccer match is packed with excitement and crucial moments; penalties, freekicks, counterattacks, goals, fouls, controversial offsides, counterattacks, and the subject of this paper: corner kicks.

Through the hundreds of events that occur each match, corner kicks are extremely tricky; players line up in different formations inside the eighteen-yard box, awaiting a cross from the player standing at the corner of the field. [4] The success of each corner kick, although not guaranteed, depends on how the players are situated, the skill and physical attributes of both attackers and defenders, and the trajectory of the ball. [12] Some teams opt to simply cross the ball into the box directly, while others try to use pattern play to work their way to the box of the field, and then capitalize. [2] According to the Stack Exchange, between 2011 and 2013, the chances that a corner kick resulted in a goal was only 3 percent and the likelihood of a shot being created was only 17 percent.

In a sport where entire tournaments depend on one goal, corner kicks have proven to be extremely useful throughout the years. In 2014, Sergio Ramon scored in the 93rd minute of the final of the largest European tournament, the UEFA Champions League, to tie the game at 1-1. His team ended up winning 4-1 in Extra-Time, just highlighting how significant these corner kicks are.

[11] Considering its immense importance to not only individual matches, but global tournaments, paired with its difficult, unexplained mastery, it's important that we answer the question: What factors lead to a successful corner kick?

[7] Subjects like deep learning and computer vision enable data scientists to find patterns amongst images and videos. [1] Applying it to soccer, a ten second clip of a corner kick can be broken down into individual frames, then analyzed to find instances of players, soccer balls, field lines, and referees. [9] With deep learning, thousands of these field representations can be broken down and used to determine which strategies lead to optimal outcomes.

This paper proposes a method to predict the success of corner kicks by analyzing player formations and ball trajectories. These factors are used to predict the eventual success of the play.

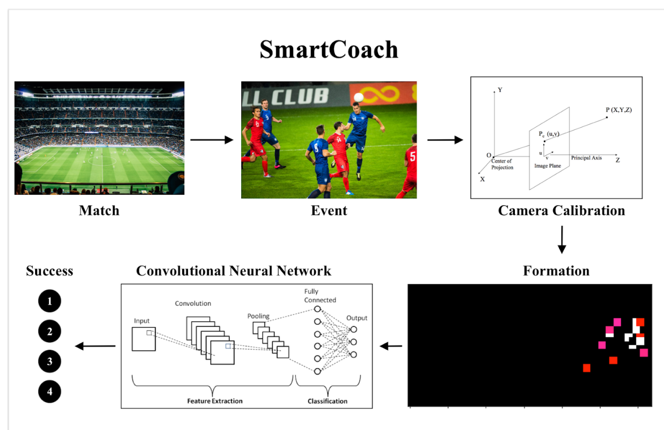

Fig. 1. The proposed model, right from the obtaining film for professional matches to predicting how formations correlate to corner kick success with a convolutional neural network.

II. Related Works

While most of the work in the applications of computer science to sports have focused on numbers, there have been a few projects focusing on computer vision.

[6], there is corresponding camera calibration and event data. [5] Their toolkit enables developers to identify the properties of the players, extract ResNet features from match film, and identify in-game events.

[8] Other work on computer vision and AI in soccer prior to this work has been with player and object tracking. [10] Data scientists, equipped with libraries and technologies

like OpenCV, can analyze the specific movements and pass trajectories throughout matches. [13] These insights enable analysts to understand how the runs and movements of a player can correlate to success in important game situations.

[15]Another important research project was done by CCBV in the domain of 2D and 2D representations. [3] With a camera's extrinsic & intrinsic parameters, a calibration algorithm can be used to calculate a camera matrix. The work demonstrates how that camera matrix can be used to take the film of a sports game, and translate the player locations, boundary lines, and referee onto a two-dimensional plane/representation.

III. Dataset

The SoccerNet public database provides film for over 500 professional soccer matches with corresponding event data. The event data provides descriptions of match events every few seconds, including corner kicks.

IV. Methodology

A. Corner Kick Segmenting

Utilizing the event data, every instance of a corner kick across 500 professional matches was analyzed. With this information, a list of over 3000 corner kicks was compiled, with corresponding 1-minute clips.

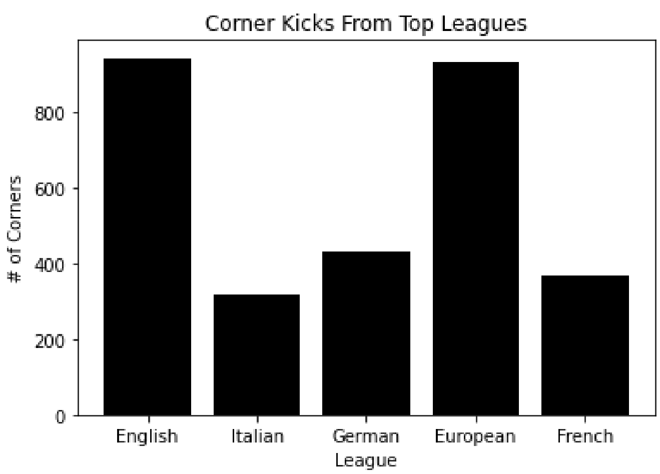

Fig. 2. The frequency of different leagues in the dataset.

B. Corner Kick Rating

To assign each corner kick a success rating, all the corner kicks were categorized into four tiers. Either a corner kick led to a successful shot on goal (4), a shot off target (3), no chance at all (2), or a turnover of possession (1). This strategy can be generalized to all corner kicks and is also an objective way of determining success.

C. Camera Calibration

The SoccerNet database includes the intrinsic and extrinsic parameters of the various camera angles. With the homography matrix, the players and field lines were mapped to their corresponding coordinates in a two-dimensional plane. Through this approach, a top-down representation of each corner kick was constructed, depicting player formations as a feature vector.

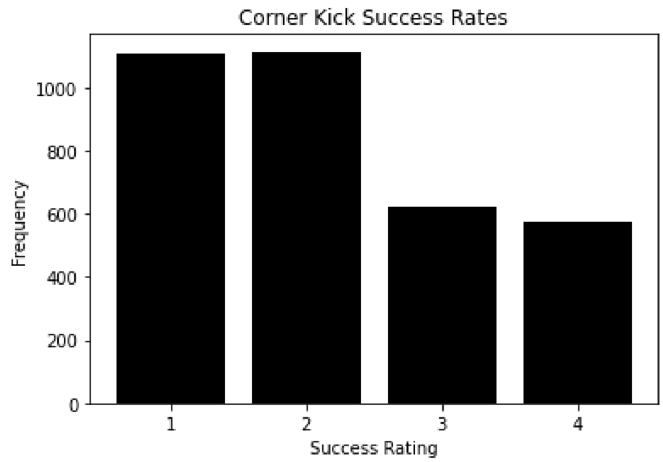

Fig. 3. The breakdown of the rankings of the 3200+ corner kicks.

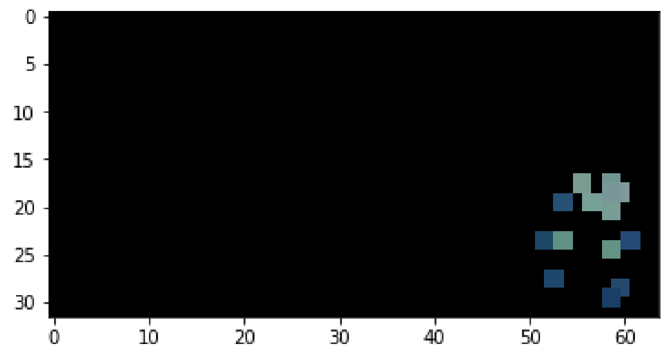

Fig. 4. The extracted top down view (with colors representing the different teams). As depicted, the players are huddled on one side of the field, preparing for a corner kick.

D. Data Augmentation

The top-down representations were adjusted to make sure there were no confounding variables in the data. Since a corner kick could be on either side of the field, some representations were flipped to make sure all corner kicks were on the right-hand side. To account for the various shirt colors of different teams and referees, the color channels of the feature vectors were standardized to consist of shades of grays.

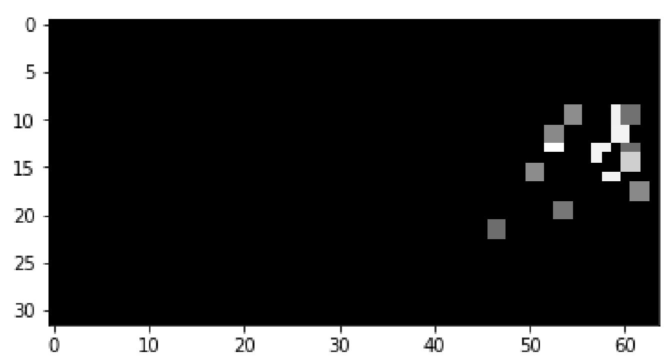

Fig. 5. The formation of players after we applied a grayscale to the image. This was to remove the founding variable of color in the neural network.

E. Passing Regions

To analyze the ball trajectories of the corner kicks to the players in the box, the field was segmented into four regions, based on field lines. Each region represents a different zone the ball was passed into; the field was split based on how the ball arrived into the 6 and 18 yard box.

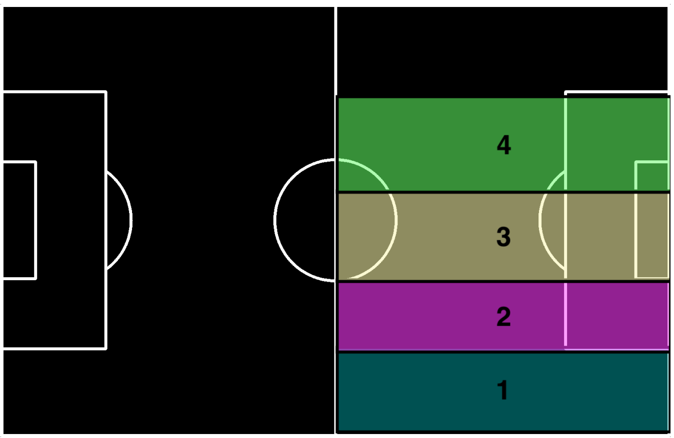

Fig. 6. The breakdown of the 'zones' or 'pass-trajectory-areas' on corner kicks. 1 represents the area closest to the corner-kick-taker and 4 represents the area furthest from the corner-kick-taker.

F. Pass Trajectories

After segmenting the field into four different zones, each corner kick was labelled to determine the pass trajectory of the play. Based on where what zone that ball was crossed into, each corner kick was given its assigned label. The majority of corners were played into the first three regions, while a few were played in region 4.

G. Final Dataset

The final dataset consisted of individual clips of corner kicks, along with the corresponding player formation feature vector, pass trajectory label, and assigned success rating.

H. Proposed Approach

Taking the player formation feature vectors as the inputs of a convolutional neural network, the various "Successes" of the corner kicks would be the output. 80% of the data would be used for training and 20% would be used for testing. The order of the corner kicks would also be randomized in each trial in order for the results to be generalizable.

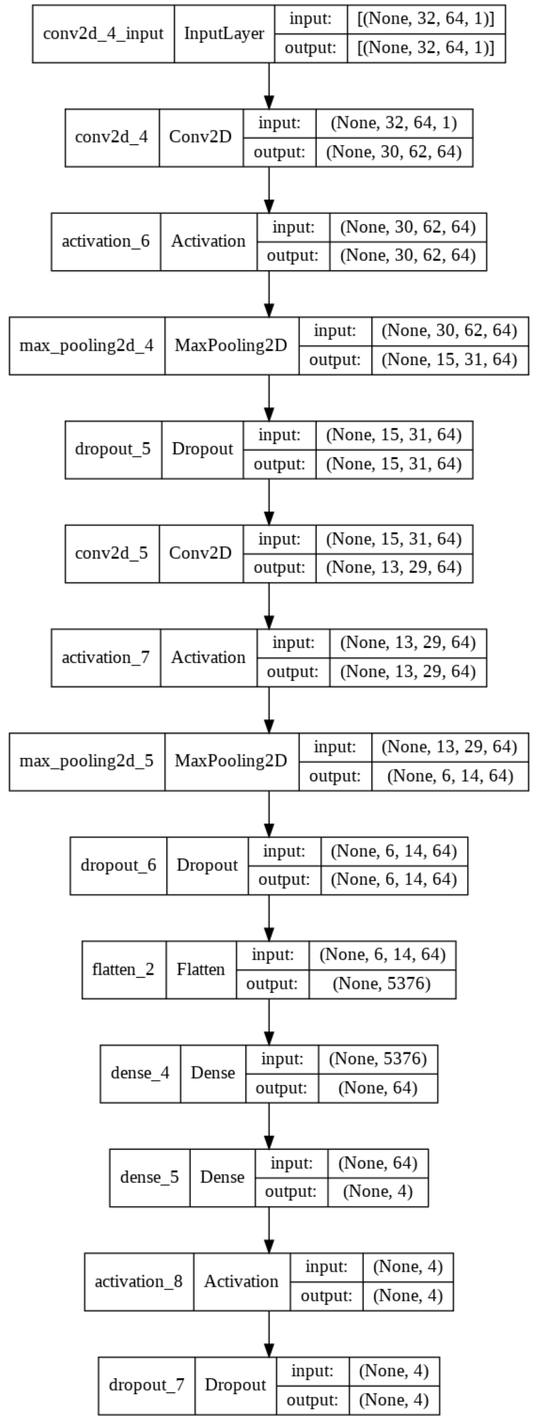

Fig. 7. The summary of the neural model that was designed for classification.

I. Architecture for Single Input Neural Network

A Sequential Convolutional Neural network was decided for the experiments. The network's input was a feature vector, representing player formations, with dimensions of (32, 64, 1). The first layer added was a Convolutional Layer, which picked apart trends/features within the feature vector. This was followed by a ReLu activation Layer. This layer enables the model to overcome the problem of vanishing gradients. Then a pooling layer was added to reduce the dimensions of the feature vectors. These first three layers were repeated a second time, followed by a Flattening Layer, which compiled all visible layers into a single layer. This was followed by 2 Dense Layers and an Activation Layer. Finally, the model was compiled with an Adam optimizer.

V. Experimental Evaluation

A. Different Experiments

Two separate experiments were utilized to analyze the corner kicks. The first experiment involved only analyzing the extreme cases of corner kicks; either a major chance created or a complete failure. This meant only using 'Success 1' and 'Success 2' classes. This experiment sought to determine if formations could be used to differentiate extremely unsuccessful or successful corner kicks. The second experiment used all four classes.

B. Formation Results

TABLE I
Accuracy of Neural Network with Extreme Cases

Trial	Training Accuracy	Validation Accuracy	F1 Score
1	78.43%	58.79%	0.4319
2	71.15%	59.34%	0.4046
3	70.85%	61.03%	0.5756

TABLE II
Accuracy of Neural Network with All Classes

Trial	Training Accuracy	Validation Accuracy	F1 Score
1	35.91%	34.68%	0.4159
2	38.29%	34.33%	0.4217
3	42.21%	35.26%	0.4141

In predicting between a very successful or very unsuccessful corner kick (2 classes), the model had a maximum training accuracy of 78.43 percent and a maximum validation accuracy of 61.03 percent, which is 10.03 percent above chance. With the 4 classes that were defined earlier, the model had a training accuracy of 42.21 percent and validation accuracy of 35.26 percent, which is 10.26 percent above chance. Additionally, these trials were all randomized in order to ensure that the experiment would be generalizable. This demonstrates that there is some correlation between formation and success of a corner kick, proving the initial hypothesis.

C. Pass Trajectory Results

To analyze how the trajectory of the ball in one of the four zones correlates to the eventual success of the corner kick, each zone was analyzed to determine the frequency of successful corner kicks amongst it.

D. Future Improvements

There is plenty more that can be done to further prove the hypothesis that the formation and ball trajectories of corner kicks affect its eventual success. For instance, more corner kicks can be added to the dataset, increasing its size from 3000. Furthermore, "Player runs" can be incorporated into the data, which will depict the movements of each individual player. For the ball trajectories, the data can be improved by simulating the pass in a 3-D environment to depict the height and spin of the ball. Making these changes will enable the model to better analyze how trends in formations and pass trajectories lead to successful or unsuccessful corner kicks.

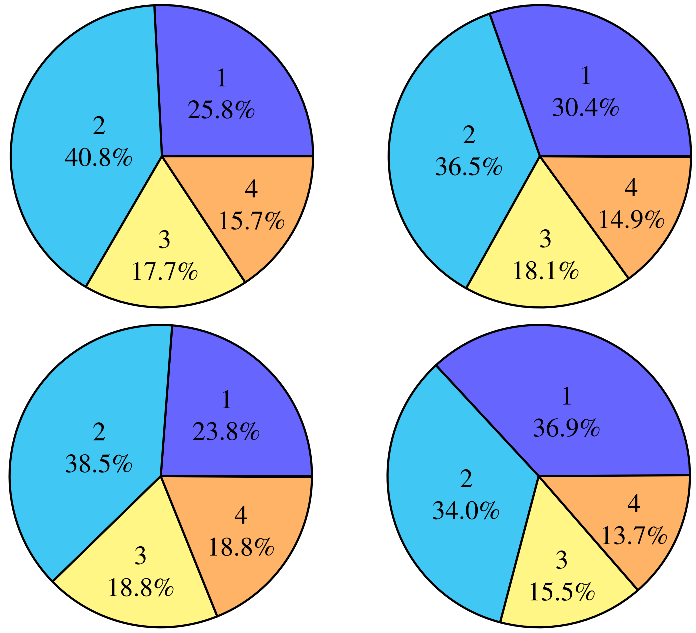

Fig. 8. This figure depicts pie-charts of each passing region(top-left: region 1, top-right: region 2, bottom-left: region 3, bottom-right: region 4). It demonstrates how the various pass trajectories affected the eventual success of the play. Independently, the pass trajectory of a corner kick did not correlate to the success of the play.

VI. Conclusion

This paper presented a way to predict the results of corner kicks, given their formation, with over 78 percent in an experiment with 2 classes. This highlights that the formations of players on corner kicks can be associated with how well the play is executed. In the future, player data, including heights and weights of athletes, can be utilized in the dataset as well, giving insight into the various other factors that play into corner kick success.

This paper's methodology can be easily expanded to other match situations as well. There are so many key moments in games, from corner kicks to free kicks to counter attacks to even penalties. This project highlights the multitude of ways it can be applied.

Furthermore, this research can be placed in the hands of youth and amateur coaches to help them design plays and formations for their own teams. Coaches will be able to use this software to analyze thousands of professional games and obtain the optimal ways to approach certain game situations. They can then take these insights and implement them throughout their own team.

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