# WHO KICKED THE BALL?

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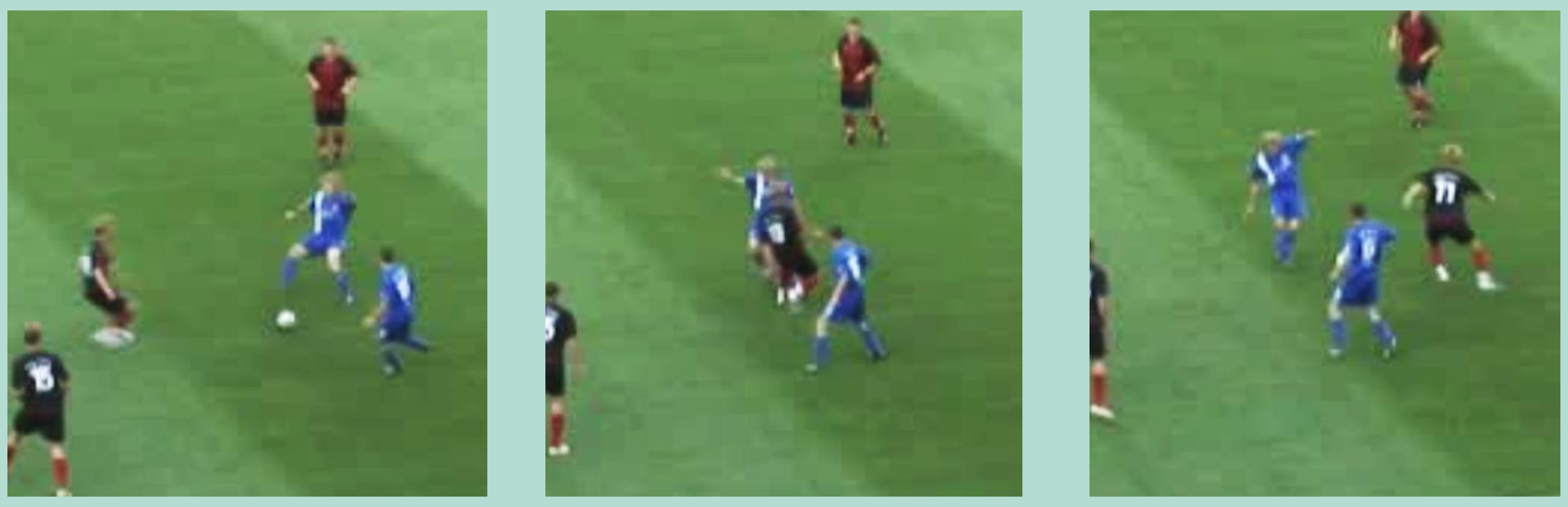
## GOAL

**When and where was the ball touched on the pitch?**
**Which foot touched the ball?**

If you would know that, you would be able to reconstruct nearly a whole soccer or another ball sports match. The automatic detection of single ball contacts was the goal of this work, as detecting all ball contacts would enable a large variety of further automatic analyses in all sorts of ball sports. A few soccer examples are:

- **Statistics:** Ball Possession, passes, dribbles, shots
- **Technical Assessment**: Left or right footedness of players
- **Tactical Assessment:** Passing networks, Compactness



It could also support human annotators, as human annotation is the state of the art method to gather event data during match play.

## PROBLEM DESCRIPTION

Given tracking data of the ball and the feet of every player, very single touch of the ball shall be detected. There are two major sources of uncertainty involved.

**Data uncertainty:**

- Mounting point of the feet transmitters
- Accuracy of the tracking system

**Rule uncertainty:**

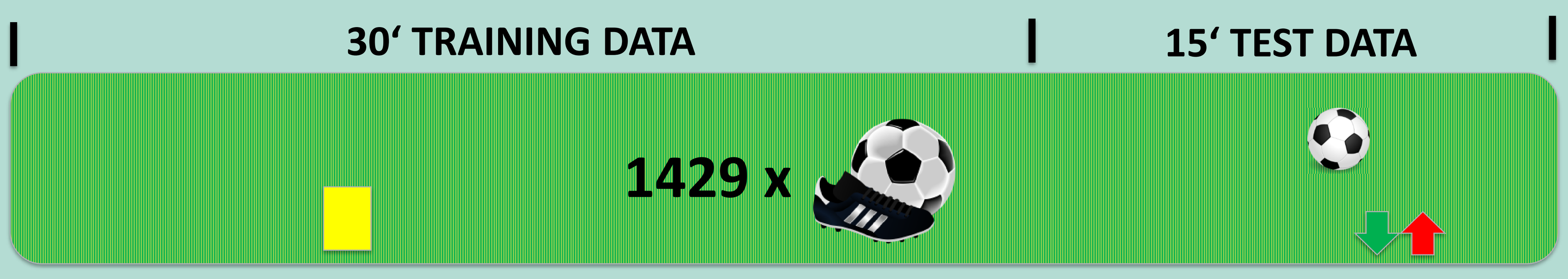
- What is the definition of a ball contact?
- What if two players hit the ball at once?

A processing pipeline needs to solve two major steps:

1. **Contact Detection** (binary classification)
2. **Foot identification** (w/ probability of contact per foot)

A probabilistic approach was chosen to keep as much information as possible for further processing.

## DATASET




We annotated time, player and foot identification (L/R) of 1429 contacts in 45 minutes of game play. Ball contacts made with the head or arms (goalkeeper) were excluded.

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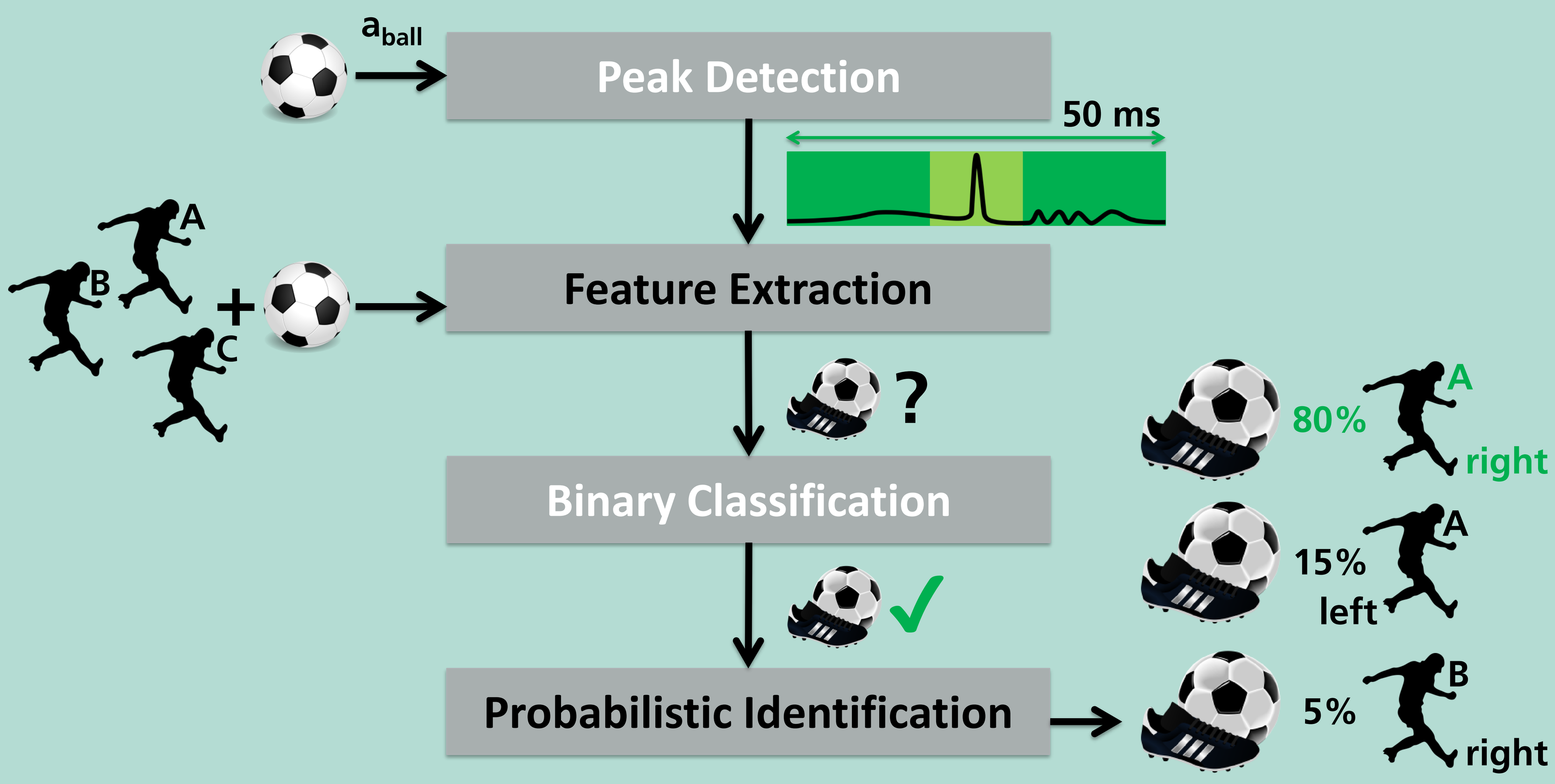
## MACHINE LEARNING APPROACH

The processing pipeline is shown below. A peak detection extracts windows centered at $t_{peak}$ using a low threshold for ball acceleration in 2D $a_{ball}$ to recognize the slightest contact. The feature extraction takes tracking data from ball and all players to compute ~86 features in a 50 ms window and also in several sub-windows symmetric to the window center.

**Examples for used features:**

- Change of direction and velocity of the ball
- Distance ball to foot, alignment of ball and foot movement




## RESULTS & DISCUSSION

**1. Contact Detection (Was there a contact?):**

In 95 % of cases we can correctly decide if the ball was hit or not. A nearest neighbor classifier leads to the best result. And even a fast and simple classifier, like a decision tree, leads to good results.

| Classifier | Precision | Recall | F1-Score |
|---|---|---|---|
| SVM | 0.98 | 0.91 | 0.94 |
| Decision Tree | 0.96 | 0.92 | 0.94 |
| k-Nearest Neighbors | 0.96 | 0.95 | **0.95** |

As we included even the slightest contacts – like contacts during slow dribbles – the results can be rated very good.

**2. Foot identification (Which foot made the contact?):**

In ~80% of cases we can correctly identify the foot that played the ball.

| Classifier | Precision | Recall | F1-Score |
|---|---|---|---|
| SVM | 0.88 | 0.74 | 0.80 |
| Decision Tree | 0.82 | 0.76 | 0.79 |
| k-Nearest Neighbors | 0.83 | 0.80 | **0.82** |

The value seems low, but there are many close scenes (e.g. duels) where even human experts have problems, or are unable to interpret the situation in real time.

## IN COOPERATION WITH

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