J-EDUCAT: Journal of Educational Studies
J-EDUCAT: Eğitim Araştırmaları Dergisi
(ISSN: 3023-8145)
http://www.jeducat,com
Published: *01.11.2026*
Article Type: *Erratum*
Related Article DOI: *https://doi.org/10.5281/zenodo.20445515*
Creative Commons Attribution 4.0 International (CC BY) License.

DÜZELTME (ERRATUM)

İlgili Makale: Futbol Oyun Görüntülerinde Otomatik Faul Tespiti için SqueezeNet Tabanlı Bir Derin Öğrenme Modeli

DOI: https://doi.org/10.5281/zenodo.20445515

Yukarıda belirtilen makalenin yayımlanan sürümünde İngilizce genişletilmiş özet (Extended Abstract) yer almamaktadır. Söz konusu eksikliğin giderilmesi amacıyla makalenin İngilizce genişletilmiş özeti aşağıda sunulmuştur.

CORRECTION (ERRATUM)

Related Article: A SqueezeNet-Based Deep Learning Model for Automatic Foul Detection in Soccer Game Images

DOI: https://doi.org/10.5281/zenodo.20445515

The published version of the above-mentioned article does not include the English extended abstract. To address this omission, the extended abstract is provided below.

EXTENDED ABSTRACT

Introduction

Football is one of the most popular sports worldwide and has evolved into a global phenomenon followed by millions of people. Although football is commonly believed to have originated in England, its earliest known form was the Chinese game “Cuju,” which was played as a military training activity during the third century BC. Over time, football spread across different regions of the world and became an organized sport with standardized rules and institutional structures. In Türkiye, the first official football club was established in İzmir in 1894 by British residents, while the first football club founded by Turks was Black Stocking in İstanbul in 1901. The establishment of major clubs such as Beşiktaş, Galatasaray, and Fenerbahçe contributed significantly to the development of football in the country. The Turkish Football Federation was founded in 1923 and later became a

member of FIFA, which itself had been established in 1904 to regulate football worldwide and organize international competitions. The continuous development of football has also led to the evolution of its rules and officiating mechanisms. The International Football Association Board (IFAB) is responsible for determining and updating the Laws of the Game to ensure fairness, safety, and consistency across all levels of football. The implementation of these rules on the field is entrusted to referees, who play a crucial role in maintaining order, enforcing regulations, and ensuring fair competition. Football referees are expected to possess comprehensive knowledge of the rules, strong communication skills, leadership qualities, physical fitness, and the ability to perform effectively under psychological pressure. As football has become faster and more complex, the number of referees involved in officiating matches has increased, evolving from a single referee to assistant referees and, more recently, Video Assistant Referee (VAR) officials. One of the most challenging responsibilities of football referees is the identification of fouls. According to IFAB regulations, fouls include actions such as kicking, tripping, jumping at, pushing, striking, attempting to strike, or holding an opponent. Such violations are penalized through free kicks or penalty kicks depending on the location of the infringement. In contrast, legal play involves clean challenges directed primarily at the ball without careless, reckless, or excessively forceful contact. Fair play principles require players to respect the rules, protect opponents' safety, and maintain the continuity of the game. However, the increasing speed of modern football, the complexity of player interactions, and the limitations of human observation make foul detection difficult. Although technologies such as VAR and goal-line technology assist referees in reviewing critical incidents, they are generally limited to situations involving goals, penalties, red cards, and mistaken identity cases. Fouls occurring outside these situations often remain dependent on the referee's real-time judgment. Recent developments in artificial intelligence and computer vision have created new opportunities for supporting decision-making processes in sports. Artificial intelligence has already been utilized in areas such as talent identification, athlete performance analysis, and injury risk prediction. Nevertheless, its application during live football matches remains limited. This study addresses this gap by investigating the use of deep learning techniques for the automatic detection of fouls in football images. Among recent advances in computer vision, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification, object detection, and video analysis tasks. Following the success of deep architectures such as AlexNet, numerous CNN-based models have been developed. However, many of these models require substantial computational resources due to their large number of parameters. To overcome this limitation, SqueezeNet was introduced as a compact CNN architecture capable of achieving AlexNet-level accuracy while using significantly fewer parameters. The architecture relies on Fire modules consisting of squeeze and expand layers, intensive use of 1×1 filters, reduced channel dimensions, and delayed downsampling strategies. These design principles enable SqueezeNet to

maintain high classification performance while dramatically reducing computational complexity. In this study, football images collected for foul detection were classified using the SqueezeNet architecture, and the obtained results were analyzed and reported.

Method

This study employed SqueezeNet, a deep learning-based Convolutional Neural Network (CNN) architecture, to classify whether a football image contains a foul or not. SqueezeNet is a lightweight CNN model designed to maintain high classification accuracy while significantly reducing the number of trainable parameters. The architecture is based on three primary design strategies aimed at minimizing model size and computational complexity. The first strategy involves replacing as many 3×3 convolution filters as possible with 1×1 filters, thereby reducing the total number of parameters. The second strategy utilizes squeeze layers to decrease the number of input channels before applying 3×3 filters. These squeeze layers perform a dimensionality reduction operation before the expand layers. The third strategy postpones downsampling operations to deeper layers of the network, allowing higher-resolution feature maps to be preserved in the early stages and improving classification performance. The fundamental building block of SqueezeNet is the Fire module, which consists of a squeeze layer and an expand layer. The squeeze layer uses 1×1 convolution filters to reduce channel dimensions, while the expand layer employs both 1×1 and 3×3 convolution filters to enhance feature representation. This structure enables the model to maintain representational power while lowering computational costs. In this research, the SqueezeNet model was initialized with weights pre-trained on the large-scale ImageNet dataset. This transfer learning approach improves convergence speed and classification accuracy, particularly when working with limited datasets. The final classification layer of the pre-trained network was modified to match the binary classification task used in this study, namely “foul” and “no foul.” SqueezeNet contains approximately 1.2 million parameters, which is substantially fewer than traditional deep learning architectures. Despite having nearly 50 times fewer parameters than AlexNet, it can achieve comparable accuracy levels. The model was implemented and trained in MATLAB. Image data were resized appropriately before being fed into the network, and the dataset was divided into training, validation, and test subsets. Model performance was evaluated using the accuracy metric.

Result and Discussion

The proposed SqueezeNet-based deep learning model was evaluated on a dataset consisting of 716 football images, including 461 foul situations and 255 non-foul situations. The dataset was divided into training and testing subsets using a 70%–30% split. The model was trained in MATLAB using the default SqueezeNet configuration with five epochs and a batch size of 64. To ensure reliability, the experiments were repeated ten times under the same conditions, and the average

results were reported. The experimental findings demonstrated that the model achieved a mean training accuracy of 97.21%, a validation accuracy of 96.57%, and a test accuracy of 95.42%. Analysis of the confusion matrix showed balanced performance across both classes without noticeable bias. The model correctly identified 90 foul images while misclassifying only two foul cases as non-fouls. Similarly, 48 non-foul images were classified correctly, with only three images incorrectly predicted as fouls. Performance metrics calculated from the confusion matrix yielded a precision value of 96.77%, a recall value of 97.83%, and an F1-score of 97.30%, confirming the effectiveness of the proposed approach in foul detection. The results were found to be consistent with recent studies in the literature that employed architectures such as DenseNet121, EfficientNetV2, ResNet50, YOLO, and Faster R-CNN for football foul detection. The achieved test accuracy above 95% indicates that the model can successfully generalize to previously unseen data. Furthermore, the small difference between training and validation accuracies suggests that overfitting was largely avoided during the learning process. The study concludes that SqueezeNet provides a reliable and computationally efficient solution for automatic foul detection in football images. Its low parameter count, approximately 1.2 million parameters, makes it suitable for real-time sports analysis applications. Future research may focus on larger and more balanced datasets, data augmentation techniques, comparative evaluations with alternative architectures, and video-based real-time foul detection systems for referee support and sports analytics applications.