Olympic Sports Events Classification Using Convolutional Neural Networks

Chapter · January 2020

DOI: 10.1007/978-981-13-7564-4_43

3 authors:

Shahana Shultana
Prairie View A&M University

Md. Shakil Moharram
Daffodil International University

Nafis Neehal
Islamic University of Technology

Chapter 43
Olympic Sports Events Classification Using Convolutional Neural Networks

Shahana Shultana, Md. Shakil Moharram and Nafis Neehal

1 Introduction

Sports are a large area of business and it has a heavy market value. For OR (operation research) models, we can consider sports as an effective application area. A huge number of sports events arranged regularly around the whole world and Olympic [1] is the world's largest sports event, and they classify their events manually which is not feasible. Classifying these sports events manually is not efficient because it is a matter of time and money. If we can classify these events automatically, it can save both of our money and time. Using deep learning approach like CNN models for sports events, classification is very advisable and feasible.

TensorFlow [2] is an example of 2G artificial intelligence and this open-source software library is developed by Google. TensorFlow supports several neural networks (CNN, RNN, etc.). In this paper, we classified five Olympic sports events using CNN models. At first, we selected five sports classes and downloaded the pictures of those classes. We used Python pillow library for image augmentation. We augmented our images to create differences from the real image, so it will be difficult to assign this image in an appropriate class. Then, we installed Inception v3 and MobileNet, which are two built-in convolutional neural network models. We just retrained our dataset with Inception v3 and MobileNet architecture. Here, we just trained the last layer of the neural network. Comparatively, Inception v3 model will be more acceptable for this type of classification for its good accuracy and it

S. Shultana (✉) · Md. S. Moharram · N. Neehal
Department of CSE, Daffodil International University, Dhaka, Bangladesh
e-mail: shahana15-5155@diu.edu.bd

Md. S. Moharram
e-mail: shakil3662@diu.edu.bd

N. Neehal
e-mail: nafis.cse@diu.edu.bd

M. S. Uddin and J. C. Bansal (eds.), *Proceedings of International Joint Conference on Computational Intelligence*, Algorithms for Intelligent Systems, https://doi.org/10.1007/978-981-13-7564-4_43

trains faster on a low processing power. Hand position, body movement, presence or absence of an object are the key factors in this case. If two or more objects are missing in an image, in this case, an image can be classified incorrectly because the model will not be able to understand the correct class for this image. For example, in the case of water polo, ball, water, hand position, etc., are the key factors.

The remaining part of the paper is arranged in the following way: Sect. 2 discusses the Related Works done before for sports analytics, Sect. 3 discusses the Methodology, Sect. 4 contains Performance Evaluation, Future Work is given in Sect. 5, and Conclusion is described in Sect. 6.

2 Related Works

Nowadays, sports are not only a part of entertainment but also a part of international business. Athletic performance is very important for sports. Victor Cordes and Lorne Olfman [3] developed a genetic algorithm functionality to predict the athletic performances. The authors collected summaries of game statics and created feature vector from player performances, used k-fold cross validation for evaluating the feature vectors, and then combined an isolated feature subset (genetic algorithm outputs) with the best fitness.

Chan et al. [4] described how to find particular types of player like defender, attacker, etc., in ice hockey. The authors used a clustering technique. They established a relationship between the types of clustered players and performance of the team by using regression model for these clusters. The authors gave a tool to assess new deals and the signing of new players, which can be used by the team managers and this is an Excel-based tool.

Ahmed et al. [5] described a method to create an excellent cricket team with the best performance and low cost. They used a genetic algorithm with several objectives and displayed a graph between net bowling average and net batting average and a decision-making tool is provided by them to arise as a successful team.

Biao Xu [6] described a genetic algorithm neural network (GANN) based system, which can predict the sports performance. Genetic algorithm (GA) is used for feature selection like weather, weight, experience, training time, height, etc., and uses backpropagation (BP) neural network for prediction. This paper used GANN for the first time to guess the sports performance.

Fister Jr. et al. [7] developed a tool, which can generate online datasets of sport activity in CSV format and the name of the proposed tool is SportyDataGen. These datasets are already processed, so preprocessing is not needed. The authors collected some real data from athletes and they wanted to add more sports class in the future for generating more sports activity.

DeSarbo W, Madrigal R [8] described the formation of a particular team, athlete, or league based on the choices of sports fans. The authors gave a procedure which is based on multidimensional scaling, collected data from university student and then performed the segmentation of fans. A few ways provided by the authors that can be used by an organization.

BJ Coleman [9] described the application of sports analytics in the research sector. The author gave a number of universities where we perform research on sports analytics.

Lucey et al. [10] described how a player role can represent the team formation. The authors analyzed near 20,000 shots and discovered almost 40% shooting percentage for "open" shots and nearly, 32% shooting percentage for "pressured" shots.

Safdarnejad et al. [11] presented a real-world dataset that contains sports videos named Sports Videos in the Wild (SVW). This dataset consists of 44 actions and includes 30 sports classes. For classifying the sports genre, the authors used three baseline algorithms (motion-based algorithm, context-based algorithm, and motion-assisted context algorithm).

3 Methodology

Our working procedures can be divided into some steps. Figure 1 shows the working steps.

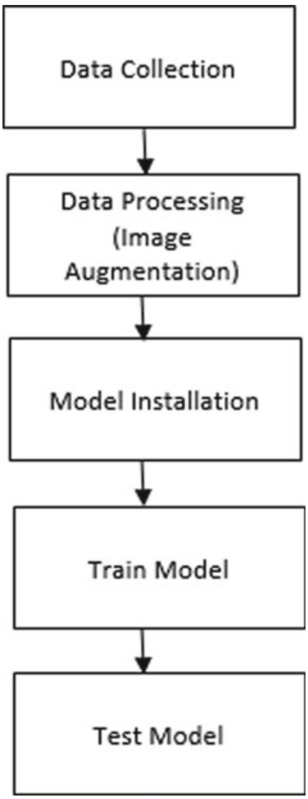

Fig. 1 Working steps

3.1 Data Collection

Select five categories/classes of Olympic sports (Badminton, Basketball, Swimming, Table Tennis, and Water Polo). Download the image data from Google images (100 photos of each class). Total $5 \times 100 = 500$ images.

3.2 Data Processing

Resize all 500 images to a specific size (200×200). Use Python pillow library for resizing. Augment all the images (Rotate $+30°$, Rotate $-30°$, Flip Horizontally, Scale the image 70%, Create a light black shade on each image). So after augmentation, from each original image, five new images are created. So, now, the total dataset is like this, per class 100 Original Image + 500 Augmented Image = 600 Image per class. As we have five classes, total images $= 600 \times 5 = 3000$ images.

From these 3000 images (600 images per class), take 20 images from each class (randomly, the image can be original or can be augmented). So, total $20 \times 5 = 100$ images. Save them in a separate folder. Name it as Test Folder. Download 50 images (10 images per class) from Google images and also save them into the test folder. Use the rest of 2900 images (580 images per class) to train the model.

3.3 Model Installation

In this work, we used two built-in models. At first, we install Tensorflow. Then, we installed Inception v3 model and MobileNet model to train our dataset.

Inception v3
Inception v3 is a built-in model, which is developed by Google for classification. Inception v3 factorized 7×7 convolutions and it has two parts: Part 1-Feature extraction from input images and Part 2-Classifies images based on their feature.

MobileNet
In this work, we also used MobileNet architecture for image classification. MobileNet is also a built-in model and in this architecture, depthwise separable convolution is used instead of conv3×3.

Resolution of Input Image

Pixel value can be 128,160,192, or 224px.

Model Size

Model size refers to the fractional value of the whole MobileNet model like 0.75, 0.50, 0.2 and in this paper we used mobilenet_0.50.

3.4 Train Model

Before starting the training, we start Tensorboard.

Inception v3

We train 2900 images (580 images per class) with Inception v3 model. The validation set is created from these 2900 images automatically. The number of training steps is 4000.

From Tensoboard, we get the graph of accuracy and cross-entropy. Figure 2 shows the accuracy graph and Fig. 3 shows the cross-entropy graph for Inception v3 model.

From the above graph (Fig. 2) we can see that the accuracy is very low for very initial step and it gradually increases for later steps. At step 4000 the accuracy is too high (almost 100%).

In this graph (Fig. 3), we see the cross-entropy loss or log loss value is high (>0.40) for very initial step and it gradually decreases for the later steps. At step 4000, the log loss value is very low (0.05).

So, Inception v3 performed this classification task very nicely.

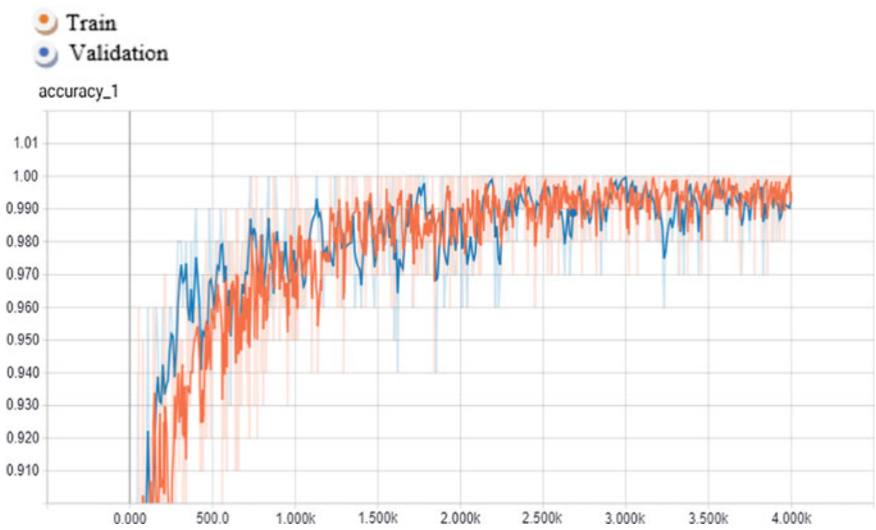

Fig. 2 Inception v3 (accuracy graph)

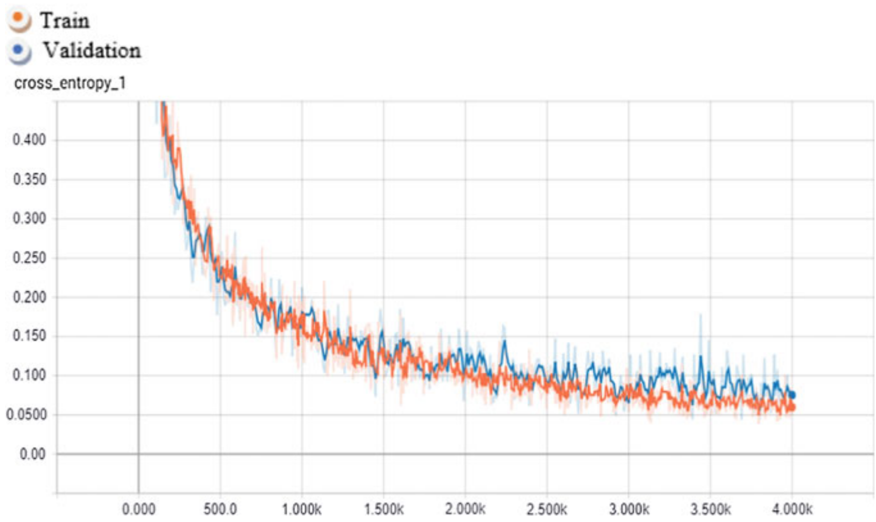

Fig. 3 Inception v3 (cross-entropy graph)

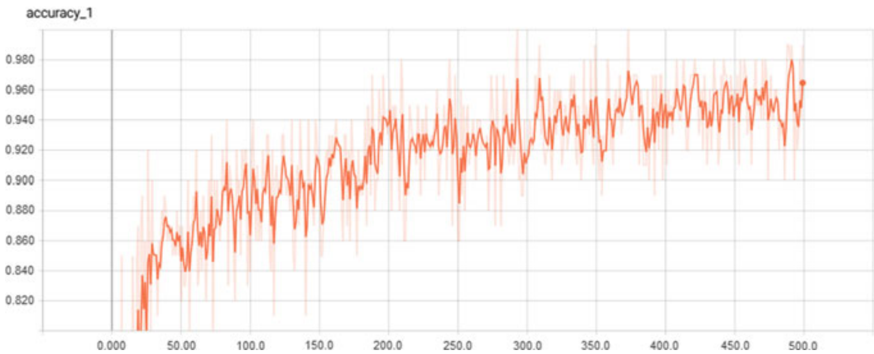

Fig. 4 MobileNet (accuracy graph)

MobileNet

We train 2900 images (580 images per class) with MobileNet model. The validation set is created from these 2900 images automatically. The number of training steps is 500, the pixel value of input images is 224px, and the model size is 0.50.

From Tensoboard, we get the graph of accuracy and cross-entropy. Figure 4 shows the accuracy graph and Fig. 5 shows the cross-entropy graph for MobileNet model.

From the above graph (Fig. 4), we can see that the accuracy is very low for very initial step and it gradually increases for the later steps. At step 500, the accuracy is very high (almost 98%).

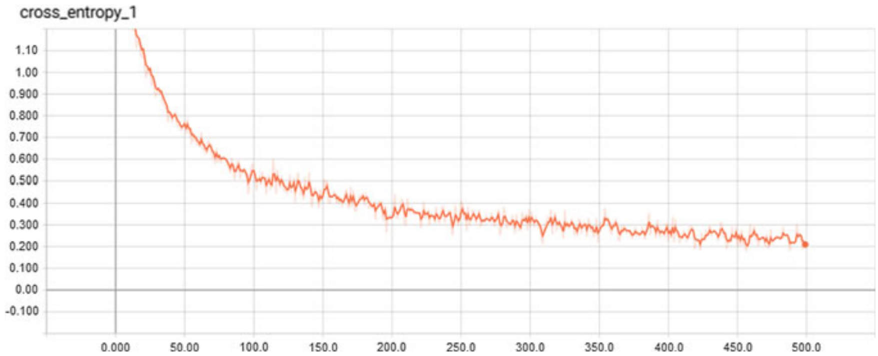

Fig. 5 MobileNet (cross-entropy graph)

In this graph (Fig. 5), the value of cross-entropy loss or log loss is high (>1.10) for very initial step and its gradually decreases for the later steps. At step 500, the log loss value is too low (0.20).

So, the performance of MobileNet architecture is very good for this classification task.

3.5 Test Model

We retrain Inception v3 and MobileNet architecture with a train dataset of 2900 images, and then we test these two architectures with our test dataset which contains 150 images (30 images per class).

Inception v3
After completion of Inception v3 architecture testing with 150 images, we get 94% test accuracy. The number of correctly classified images is 129 and incorrectly classified images is 21.

MobileNet
After completion of MobileNet architecture testing with 150 images, we get 90% test accuracy. The number of correctly classified images is 113 and incorrectly classified images is 37.

4 Performance Evaluation

From test result, we get the confusion matrix for Inception v3 and MobileNet model. Confusion matrix gives the performance measure of Inception v3 and MobileNet model (Tables 1, 2).

Table 1 Confusion matrix of inception v3

Actual	Predicted					
		Badminton	Basketball	Swimming	Table tennis	Water polo
	Badminton	25	0	0	5	0
	Basketball	1	28	0	1	0
	Swimming	0	1	24	0	5
	Table tennis	4	0	0	26	0
	Water polo	0	0	4	0	26

Table 2 Confusion matrix of MobileNet

Actual	Predicted					
		Badminton	Basketball	Swimming	Table tennis	Water polo
	Badminton	22	2	0	6	0
	Basketball	0	26	4	0	0
	Swimming	0	1	27	1	1
	Table tennis	9	0	1	20	0
	Water polo	0	1	11	0	18

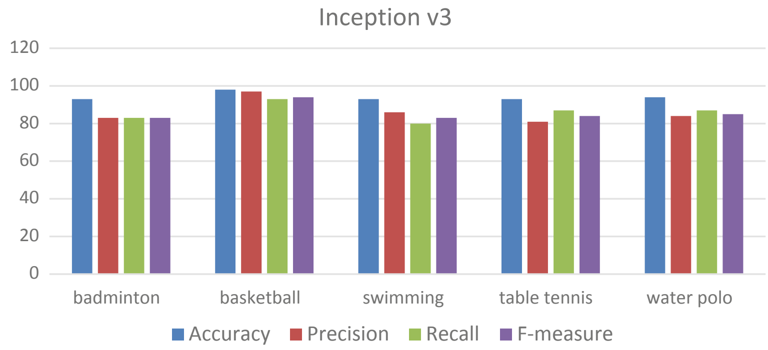

Fig. 6 Inception v3 (Accuracy, Precision, Recall, and F-measure)

We get 94% test accuracy for Inception v3, macro average precision of 0.862, macro average recall of 0.860, and macro average F1 score of 0.860. From these five classes, we get the best accuracy for basketball 98%, then for water polo 94, and 93% accuracy for the rest of three classes. Only 21 images out of 150 are incorrectly classified. Figure 6 shows the test accuracy, precision, recall, and F-measure of the classes using Inception v3 model.

We get 90% test accuracy for MobileNet, macro average precision 0.779, macro average recall 0.753, and macro average F1 score 0.753. From these five classes, we

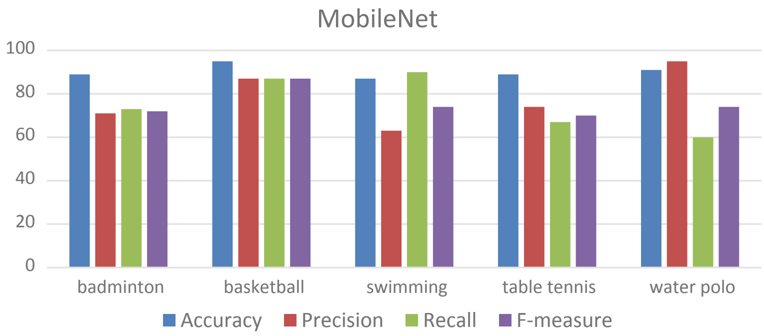

Fig. 7 MobileNet (Accuracy, Precision, Recall, and F-measure)

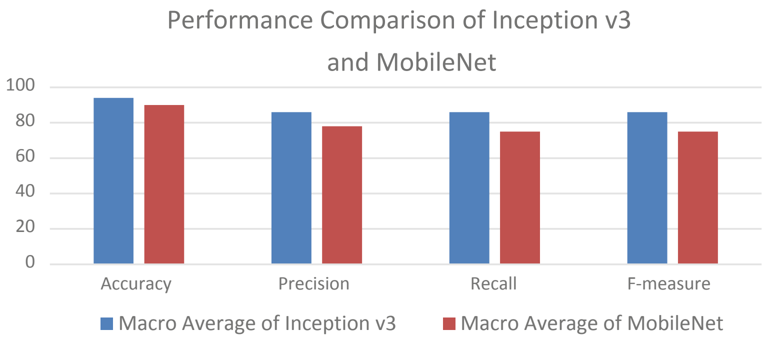

Fig. 8 Performance comparison between these two models

get the best accuracy for basketball 95%, then for water polo 91%, for badminton and table tennis 89%, and for swimming 87%. 37 images out of 150 are incorrectly classified. Figure 7 shows the test accuracy, precision, recall, and F-measure of the classes using MobileNet model.

We can compare the macro average accuracy, precision, recall, F-measure of Inception v3, and MobileNet and from this comparison, it is clear that the performance evaluation of Inception v3 is better than MobileNet. Figure 8 shows the performance comparison between Inception v3 and MobileNet.

For evaluating the test performance, receiver operating characteristic (ROC) curve of both (Inception v3 and MobileNet) architectures are generated. Figure 9 shows the ROC curve of Inception v3 and Fig. 10 shows the ROC curve of MobileNet.

ROC curve of Inception v3 provides 91% area for badminton, 100% area for basketball, 97% area for swimming, 95% area for table tennis, and 99% area for water polo.

ROC curve of Inception v3 provides 91% area for badminton, 100% area for basketball, 97% area for swimming, 95% area for table tennis, and 99% area for water polo.

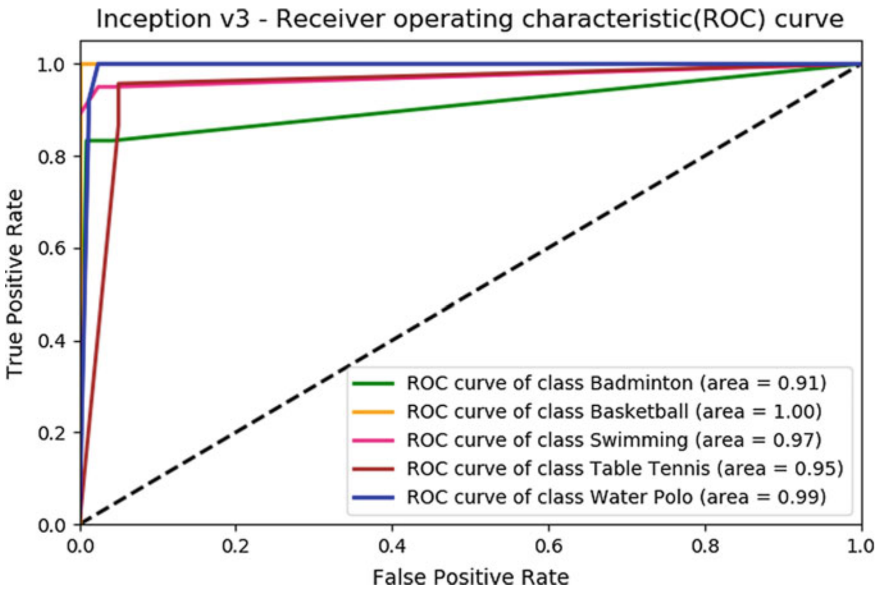

Fig. 9 ROC curve of inception v3

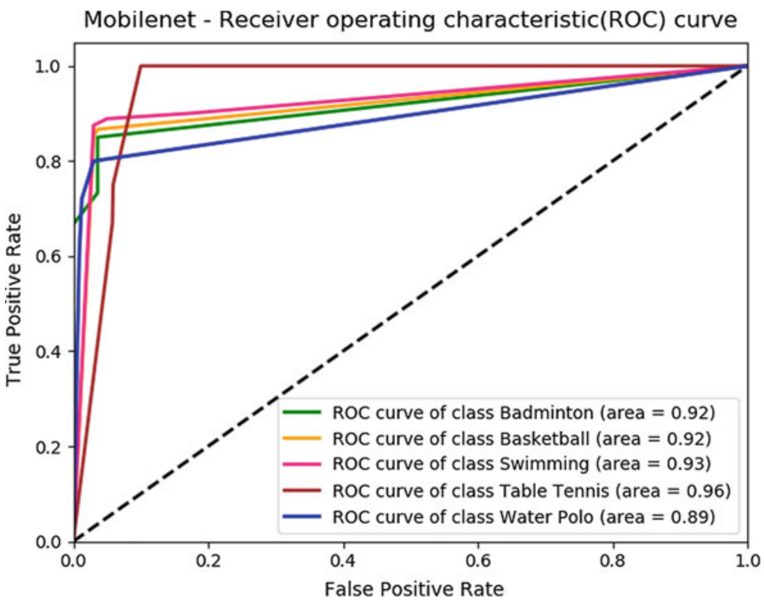

Fig. 10 ROC curve of MobileNet

ROC curve of MobileNet provides 92% area for badminton, 92% area for basketball, 93% area for swimming, 96% area for table tennis, and 89% area for water polo.

Among the five classes Inception v3 gives more ROC AUC (area under the curve) for basketball, swimming, and water polo. On the other hand, MobileNet gives more ROC AUC (area under the curve) for badminton and table tennis. Inception v3 gives better accuracy for three classes and MobileNet gives better accuracy for two classes. So, the correct classification rate of Inception v3 is greater than the correct classification rate of MobileNet.

5 Future Work

In this paper, Inception v3 and MobileNet architectures provided by Google are used. We intend to train and test our dataset using these models to get better accuracy. But Inception v3 and MobileNet are built-in model. So we plan on creating another model and train it with the same dataset so that we can get a more accurate result and can beat the accuracy of the models used in this paper. So, in future, we want to create a CNN (convolutional neural network) model to get much better accuracy.

6 Conclusion

Throughout the paper, Inception v3 and MobileNet both are classified dataset appropriately. There are only a few cases where these models predicted wrong classes. But Inception v3 architecture gives better results than MobileNet, because Inception v3 correctly classified 129 images out of 150, whereas MobileNet correctly classified 113 images out of 150. So we can say that Inception v3 architecture is more accurate. Contrariwise, in ROC curve, Inception v3 gives more AUC for all classes. But only for two (badminton and table tennis) classes, the AUC in ROC curve of MobileNet is higher than the AUC in ROC curve of Inception v3, although for these two classes MobileNet provides only 1% extra AUC than Inception v3. However, both (Inception v3 and MobileNet) models are good for classification.

References

1. Dr. Ray Stefani (2016) Olympic sports of the future. Sport J 20. ISSN:1543-9518 (Electronic). Accessed 30 Mar 2016
2. Martín A, Ashish A et al (2016) TensorFlow: large-scale machine learning on heterogeneous distributed systems. CoRR abs/1603.04467 (2016)
3. Cordes V, Olfman L (2016) Sports analytics: predicting athletic performance with a genetic algorithm. In: Twenty-second Americas conference on information systems, San Diego

4. Chan TYC, Cho JA, Novati DC (2012) Quantifying the contribution of NHL player types to team performance. Interfaces 42(2):131–145
5. Ahmed Faez, Deb Kalyanmoy, Jindal Abhilash (2013) Multi-objective optimization and decision making approaches to cricket team selection. Appl Soft Comput 13(1):402–414
6. Xu B (2012) Prediction of sports performance based on genetic algorithm and artificial neural network. Int J Digit Content Technol Appl (JDCTA) 6(22):141–149
7. Fister Jr I, Vrbanciˇ c G, Brezo ˇ cnik L, Podgorelec V, Fister I (2018) SportyDataGen: an online generator of endurance sports activity collections. In: 29th CECIIS, Varaždin, Croatia
8. DeSarbo W, Madrigal R (2012) Exploring the demand aspects of sports consumption and fan avidity. Interfaces 42(2):199–212
9. Coleman BJ Identifying the "players" in sports analytics research. Interfaces 42(2):109–118
10. Lucey P, Bialkowski A, Carr P, Yue Y, Matthews I (2014) How to get an open shot: analyzing team movement in basketball using tracking data. In: 8th MIT sloan sports analytics conference, Boston
11. Safdarnejad SM, Liu X, Udpa L, Andrus B, Wood J, Craven D (2015) Sports videos in the wild (SVW): a video dataset for sports analysis. In: 11th IEEE international conference and workshops on automatic face and gesture recognition (FG), Slovenia
12. Tensorflow Tutorials (2018). https://www.tensorflow.org/tutorials/images/image_recognition. Accessed 7 Sept 2018
13. Towards data science homepage (2018). https://towardsdatascience.com/review-mobilenetv1-depthwise-separable-convolution-light-weight-model-a382df364b69. Accessed 2 Oct 2018
14. Becoming human homepage (2018). https://becominghuman.ai/transfer-learning-retraining-inception-v3-for-custom-image-classification-2820f653c557 Accessed 2 Oct 2018
15. Medium homepage. https://medium.com/greyatom/performance-metrics-for-classification-problems-in-machine-learning-part-i-b085d432082b. Accessed 13 Oct 2018