Detecting Third Umpire Decisions & Automated Scoring System of Cricket

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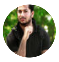
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Detecting Third Umpire Decisions & Automated Scoring System of Cricket

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Abstract—: **For the time being, Cricket is an indisputably one of the most interesting game in the world, especially in the territory of South Asian. As human beings are prone to error, sometimes errors have happened to an umpire and about a constant time is taken by the third umpire for an exact decision of a review. The two different domains artificial intelligence and computer vision have become pop in cricket analysis and decision making. Using different types of computer vision's procedures in exploring several Cricket cases and automatically turning into decisions have become exoteric in recent days. In this research paper, we have propounded a classification method by the aids of Convolutional Neural Network (CNN) with Inception V3 in order to automatically unroll the decisions of third umpire and scoring system such as umpire signal detection. We have also proposed the deep CNN technique that aids to increase the performance of CNN.**

Index terms—***: Third Umpire decision, Automate Scoring System, Deep CNN, Inception V3, Cricket.***

I. INTRODUCTION

Cricket is not only a national game but also international game where played among two teams of 11 players. In this game, every legal or illegal ball is calculated crucial moment because every ball is the game changer in any match. Cricket is a 'Gentleman's Game' but nowadays it has increased incidents of match-fixing, cheating sledding. In the beginning 1963, Cricket uncovered a new era, when it proposed a limited overs match where each team batting and bowling at least one innings. An umpire is a crucial moment in a match of cricket. So Every Cricketer and umpire should abide by the 42 rules in this game. In this game, two umpires stand on the field whose declare many decided in matches. If some decisions (such as run-out, lbw, stamping, six or catch) during a match, the on-field umpire cannot choose the right decision he used to call another umpire whose name is the third umpire. When a fielder or bowler cannot abide by the umpire's decision they called the third umpire. In cricket, it is a challenge to build such technology that has ability for deciding the third umpire in exact time with high accuracy. In this research paper, we discovered an automatically third umpire decision making via the help of novel technology in a cricket game. By using a set of automatic filmed videos, we would easily find the outcome taken by a third umpire and made an automated scoring system by the signal detection of umpire decision. We have developed the introduction of a specific model an inception v3 which is made by Google to classify a third umpire decision. Also, we have applied the deep learning method as different CNN's layer to get a higher order most correct decision. The final layer of inception v3 model where hyper-parameter from other layers stay contact. Our proposed method is looking for to operate better and less costly due to any infrared sensors and other devices.

The contributions are summarized as follows:

- Classifying the third umpire decisions of cricket.
- Automate scoring system by detecting umpire signal.
- CNN and Inception V3 are imparted as classification algorithm and deep CNN is used in order to improve the result.

The rest of paper is organized as follows; we define and formulate the background study in Section 2. Section 3 reviews the related work. We present our methodology in Section 4. We give an overview about the experimental results and obtained results are used in our model.in Section 5 and Section 6, respectively. In Section 7, We discuss our improve model. We report the final results in Section 8 .We also summarize the experimental tools in Section 9.Finally; Section 10 highlights the future work.

II. RELATED WORK

Modern techniques are founded on Convolution Neural Network (CNN) and automatic representation learning are taking maximum credit[1] which is due to their ability to study useful visual representation(VR). The raw data can observe one from another object fully accurately. Applying the transfer learning technology along with Inception-v3 model which training a CNN model. This model used image dataset for recognition purpose Bangladeshi Sport [2].The spatial images shapes is very efficient image classification problem [3] which is used by CNN model. The analysis of cricket videos is developed by CNN model that have been achieved action recognition. Some of the functions of this domain include image processing techniques that make use of the third umpire for decision-making to be used for run-out wicket surveillance [4]. To determine whether the ball was no ball or legal, the bowling crease applied to two areas and the applicable image subtraction method [5] and a multi-valued automated decision whether a ball is no-ball or wide ball [6] that is also help of a single smartphone camera [7]. A bowler's deliver is going to be no ball if the bowler's heel front foot or opposite of popping crease [8].The reality of incited cricket that implementation of multi valued automated decision making which detect wide and no ball [9].There are several algorithms such as support vector machine (SVM), histogram of gradients (HOG), and contour detection which are used by ball tracking, and many decisions for LBW, wide, bouncer and no ball [10].To analysis the bowling turning, bowler's variations used by advanced technology algorithms called Hawk Eye [11].

III. BACKGROUND STUDY

A. Cricket

Nowadays Cricket is undoubtedly worldwide and one of the most popular games where a single delivery can turn the luck of the game. This game provides two teams, for example Team A and Team B on a field which is a rectangular area of a 22 yards pitch is urged for bowling and batting. At both ends of the pitch, there are two areas named by white lines in a similar way. They are named as creases. In the middle of per crease, three wooden stumps are planted. They are collectively named the wicket. Based on the result of a toss, one team, say Team A is choice batting (by using a wooden structure called a bat) or balling (by using a special type of a ball). If Team A chose to bat the other team says Team B automatically balling. Every phase of the game is called as an innings. When a match is played, the batting team and opponent teams wicket-keeper wear extra dresses called Helmet(wearing head), Pad(wearing legs), Gloves(wearing hand).There is the various format in cricket such as Test matches, One-day International(ODI), twenty20(T20). In the test matches are played over five days with unlimited overs and each teams batting for two innings of unlimited length. Also, these match the players wear a white dress. In ODI cricket played one day with 100 overs and each teams batting for one inning of 50 overs. In other words, T20 cricket played few hours where each team played 20 overs. Both ODI and T20 games the players wear colorful dresses. In this game, the match is controlled by two on-field umpires, aided by a third umpire and match referee.

IV. METHODOLOGY

In this paper, we have recited the classification techniques which need to take third umpire judgment in the field of cricket. In many ways, it is common that the main umpire and leg umpire flunk to determine their sign or flunk to take an exact decision. In these situations, the third umpire takes the power for making the decision. But it takes lots of time in order to take judgment. To recovery this delay, third umpire decisions can be taken artificially at instance time and automate scoring system by classification using CNN and Inception V3. This section of the paper narrates the technique of CNN and the method of applying pre-trained Inception V3 way in niceties. We have also developed the techniques of umpire signal classifications that assist to the automated scoring system. The workflow is delineated in figure 1.

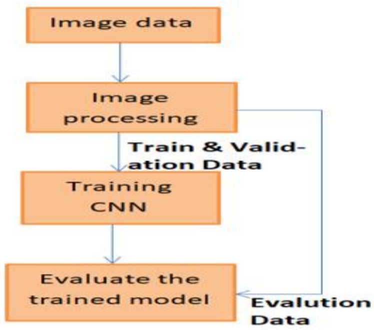

Fig. 1. Workflow diagram.

A. Datasets

We compiled such datasets of cricket which almost need to take third umpire decisions. We collected 6 types of datasets and a more dataset of umpire in order to automate scoring system by classification umpire signal. The whole datasets contain RGB image and formatted in .jpg extensions. We have detruncated the whole dataset into 80% training set and 20% test set. The collection view of data is given bellow via table.

Name	Total	Training	Test
Foot cross No Ball	633	506	127
Waist height No ball	617	494	123
Bounce Ball	646	517	129
LBW	719	575	144
Run Out	367	294	73
Stumping	672	538	134

Table 1. Data of third umpire decisions.

For the detection of umpire signal, we gathered total 2479 images of different signal of umpire. 2983 images are separated for training set and 496 images are for testing set for the sake of automates scoring system.

Name	Number of Data
Out	229
Four	221
Six	214
Bye	203
Leg Bye	208

One Bounce	230
Wide	198
No Ball	205
Dead ball	187
Cancel Call	224
New Ball	175
Penalty Run	185

Table 2. Image of umpire signal

B. *Image Pre-Processing*

All the collected data sets were normalized to enable in propounded model. Some normalization tasks were competed for committing them usable to perform in model. At first, all the data or images were resized to 227*227*3 from the regulation of dimension to fit in our proposed system. All the images have been arranged in five kinds of ways such as revolve left -45 degree, revolve right +45 degree, flip-up horizontally about X-axis, and shear by a particular measurement, revolve left -30 degree.

Basically, the whole image whitening was accomplished applying the Principal Component Analysis (PCA) system. In recently, a substitute named ZCA displays a better outcome and the outcomes is disposed images that holds all of the real dimensions and unlike PCA, the consequence disposed images still similar to their main images. In our datasets, there were lots of data might not in center of the frame. In this case, Sometimes the classification goes to wrong. To recover this bad situation, the images were shifted into center. In order to turn all data horizontally, we have put the width in the limit to 0.3 also for vertically, the width turning limit is 0.3.

C. *Convolutional Neural Network*

The CNN or ConvNet is the abbreviation name of Convolutional Neural Network which is a category of deep learning, feet-forward Artificial Neural Networks (ANN). The CNN is popular for visualizing image and classification as a category of images. The good diagram multilayer perceptron's are required as minimal pre-processing by the variation of CNN's. They are also familiar turning invariant or dimension invariant of ANN [12]. CNN allow us to analysis image architecture and encode it to a specific property based on invariance characteristics [11, 12]. These procedures create the forward function with more proficient to performance and extremely minimize the volume of parameters in the network. The layers' details in the CNN applied in proposed method is given below.

1) *Rectified linear unit:* ReLU is one kind of activation function that is basically applied in the area of deep learning networks for hidden layers. When the input of a function is less than 0, it returns 0 and for greater than 0 the output is not different from the input. Its derivative is either 0 or 1. When the input is positive the derivate is nothing but 1 so there is no squeezing effect on back propagated errors. It can be defined as R(x) = max(0, x), here x is the input to a neuron.

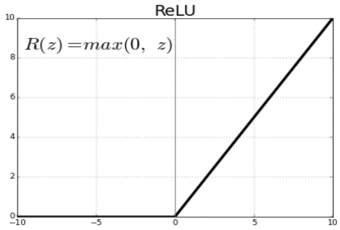

Fig. 2. Rectified Linear Unit

2) *Convolution Layer:* The convolution layer is generally considered as initial layer for CNN where the image are convolved. In general, by the help of filters units that we apply across the data through a sliding window the depth of the filter is the equal as the input so for a color image. It is essential to remember that convolution is not only applicable to images though we can also conventional time series data. Mathematically, consider a one-dimensional convolution if input F and kernel g are both functions are one-dimensional data like time series data then their convolution is given by this equation

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau).g(t-\tau)d\tau$$

It looks like fancy math but it has to mean the equation represents the percentage of area of the filter G that overlaps the input F at a time tau overall time T since tau less than zero is meaningless and tau greater than T represents the value of a function in the future which can apply tighter bounds to the integral

$$(f * g)(t) = \int_{0}^{t} f(\tau).g(t-\tau)d\tau$$

In other words, three hyper-parameters maintain the dimension of the output adapter such as depth, padding, and stride. The Output Size of a convolutional layer is:

$$o = \left(\frac{n+2p-f}{s} + 1\right) * \left(\frac{n+2p-f}{s} + 1\right)$$

Here p, s, f, n, o refer consequently padding, stride, number of filters, image width or image height, output size (w*h).

3) *Activation layer:* The AL only nonlinear activation functions are applied between subsequent convolutional layers this is because there won't be any learning if we just use linear activation functions

A_1*(A_2*X)=(A_1*A_2)*X=A*X

Let's consider a1 and a2 be two subsequent convolution filters applied without a nonlinear activation between them because of the associativity property of convolution these two layers are effective as just a single layer the same holds true for typical ANN.

4) *Max Pooling Layer:* It is a normal discretization action which is work by describing a max filter to (usually) non-overlapping an area of the fundamental representation. It takes the highest value from each sub-region of every node at the previous layer. Max pooling discards 75% of the activations and controlling over fitting. The Output dimension of a MaxPooling layer is:

$$O = \left(\frac{nw-f}{s} + 1\right) * \left(\frac{nh-f}{s} + 1\right)$$

Here, s, f, nh, nw, and o refer consequently stride, number of filters, input height, image width, and output size (w*h).

5) Dropout Layer: A dropout layer puts the input component to 0 by using probability. Dropout is a methodology that is urged to develop over-fit on ANN.

6) Fully Connected Layer: The FC layer is an important term in the CNN and it is narrated the properties of a vector for the inserted data. This property of the single matrix takes information that is significant to the input. The result from the convolution layers illustrates a significant level of property in data and when the outcome might be flattened and related to the outcome layer affixing a fully connected layer is ordinarily a cheap method of learning linear or non-linear combinations of these elements important layers. Such as providing significant, low-dimensional, invariant element space. So, the FC layer is learning perhaps nonlinear operation in that dimension so that we can convert the outcome of a pooling layer to input for the fully connected layers.

7) Softmax Layer: Softmax allots decimal probabilities to every group in a multi-group task. Those decimal probabilities need to be added up to 1.0. This additional constraint aids training converge more perfectly and significantly.

$$\sigma(x_j) = \frac{e^{x_j}}{\sum_{j=1}^{n} e^{x_i}} \quad \textit{Where } i,j=1,2,3....n$$

8) Cross-entropy loss: The other name log loss, determines the action of a grouping process and its result is a likelihood rate between 0 and 1. Cross-entropy loss enhances as the forecasted probability diverges from the actual label. In our classification process to classify cricket decisions based on images of the target image, a very common type of loss function to use is Cross-Entropy loss. If P (x) is the entropy of y. *Dkl* (x‖y) is the Kullback-Leibler divergence of y from x then it is defined as P (x, y) = *E*x [−logy] = P (x) + *Dkl* (x‖y)

The graphical views of our CNN model is given below.

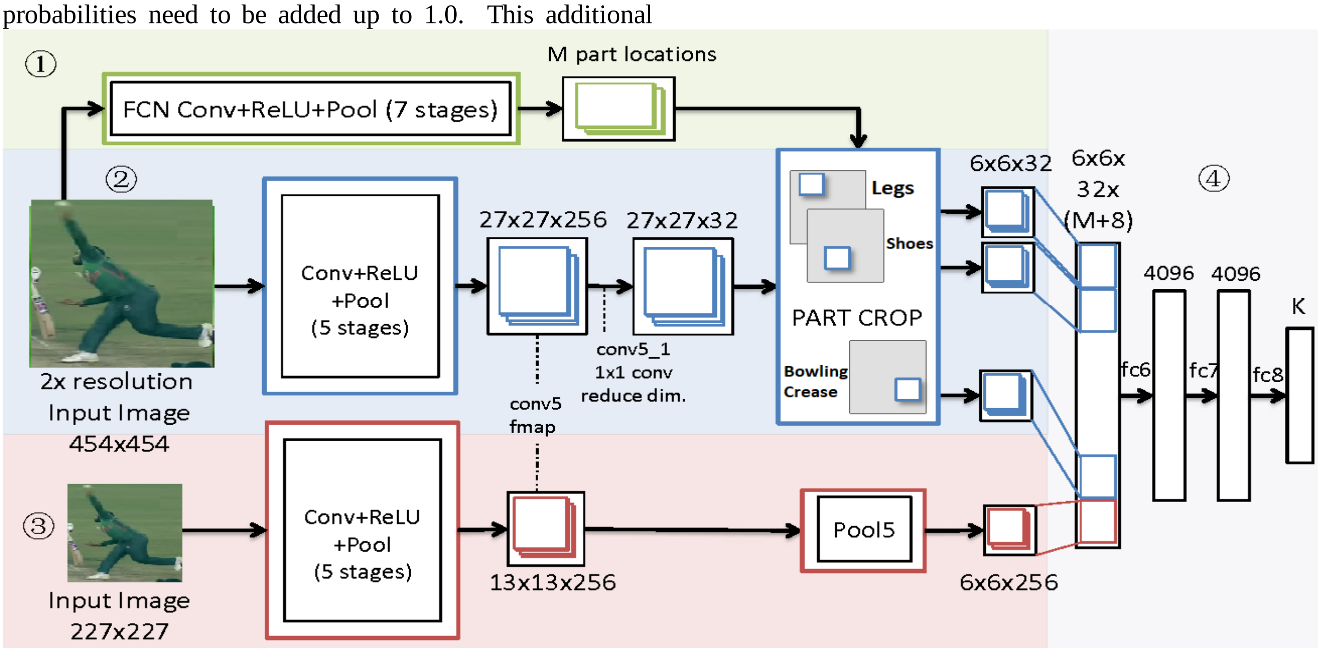

Fig. 3. Architecture of proposed CNN Model.

D. Inception V3

It was a project of Google people in 2015 and utterance of Google's Inception architecture for the separation of image in group. It is a really grand technique and innovation and it's the output of several cycles of trial and error. The Inception [13] code exerts TF-Slim, that looks to be one type of abstractiveness module over TensorFlow that creates writing CNN nets easier and more suitable. This technique can be trained on a set of the ImageNet database, that is applied in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). The model has been trained on more than a million images and can separate photos into thousands of groups, for instance, cat, dog, cow, and others. Hence, the technique had informed height elements representations for a massive range of images.

There are three procedures for using CNN [14]. Transfer learning has been applied and it is based on the idea, that the sense of resolving one type of task can be urged in order to resolve a resembling task. Applying the inception v3 method to separate images by training which is another type of transfer learning. We slightly changed the inception V3 by shifting the first four layers of the stem, up to and including the MaxPool, as well as deleting the auxiliary network. We modified the Average Pool dimension to 10 × 6 to mirror the alteration in activations. We tried including the stem and deleting the initial stride of 2 and MaxPool but got that it accomplished worse than the variant with the truncated stem.

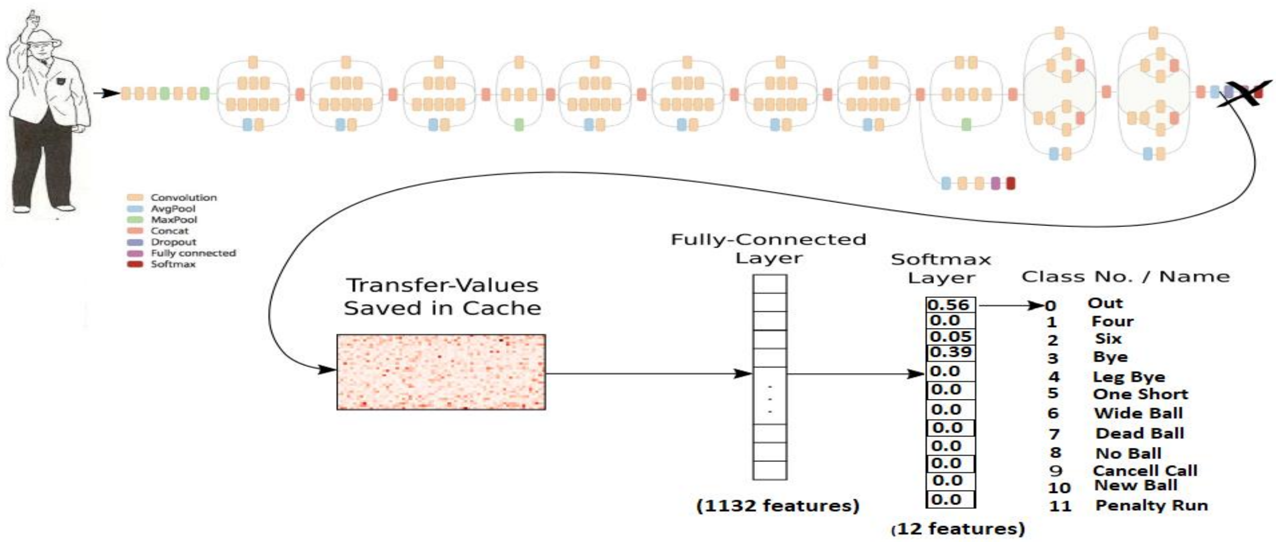

Fig. 4. Proposed Inception V3

E. Model Optimization

A model optimization system is petitioned in order to create the proposed system more sufficient and unfailing to inserted data. In this deep learning way, here also has been petitioned some optimization methods. Applying the SGD in order to compile the method as an optimizer. Stochastic Gradient Descent (SGD) has been enacted as a parameter for each training instance. It is a lot of adequate methods. Generally, it has taken an unaccompanied change at each movement. The right taste for cost function optimization is cross-entropy. The most familiar cost function of cross-entropy is a regularization method. To perform the best separation and forecasting in ANN, this operation is applied massively. Here showed groupies cross-entropy as a loss function.

$$L_i = \sum_j t_{i,j} \log(p_{i,j}) \quad where\ i,j = 1,2,3 \ldots .n$$

V. EXPERIMENTAL RESULTS

In this recipe, we have recounted and compared various consequences that founded in our tests.

A. Evaluation of Model

The whole proposed datasets have been separated into three portions such as training, validation, and evaluation. The two parts, training and validation sets have been applied at the moment of training of the CNN system. After the training completing the evaluation, data has been used to measure the performance of the model that was trained. To determine the accuracy the law is followed

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

VI. OBTAINED RESULTS

After performing and trained the models, the results have been noted in the table

Name	CNN Accuracy (%)	Inception V3 Accuracy (%)
Foot cross No Ball	74	84
Waist height No ball	77	85
Bounce Ball	68	81
LBW	56	63
Run Out	53	69
Stumping	54	70

Table 3. Obtained Results.

From the table, we can analysis the outcome of proposed conventional neural network (CNN). The noted results are for the third umpire decisions datasets. But we have obtained 83% accuracy in CNN for the classification of umpire signal that aid for automatic scoring system accurately.

VII. IMPROVE MODEL AND RESULT

In order to obtain a more accuracy in our propped model, we have affixed a deep learning model that is Deep Conventional Neural Network (DCNN). There are two options to transfer our CNN to DCNN the first one is to add another conventional layer and second option is add another fully connected layer. In our experiments, we have added a conventional layer to our previous neural network.

VIII. FINAL RESULTS

Name	CNN Accuracy	Deep CNN	Incep.V3 Accuracy
Foot cross No Ball	74%	82%	91%
Waist height No ball	77%	83%	90%
Bounce Ball	68%	79%	88%
LBW	56%	61%	69%
Run Out	53%	67%	79%
Stumping	54%	68%	77%

Table 3. Final Results

Form the table, it can be showed that the DCNN performance wide more than CNN But Inception V3 supplies almost best result from others.

Fig. 7. detection of fair ball and no ball

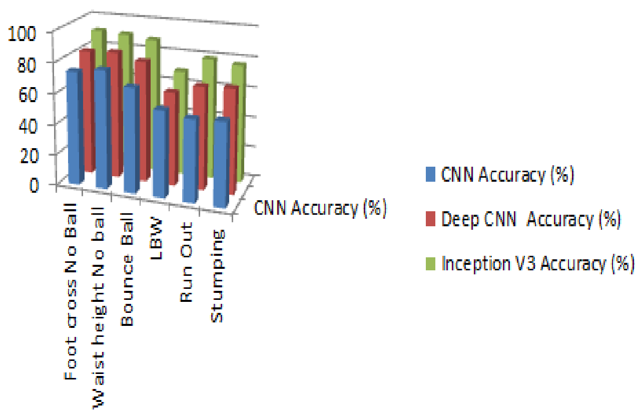

Fig. 5. Performance of third umpire decision

Its hold 94% accuracy in Deep Conventional Neural Network (DCNN) and 100% in Inception V3 for the classification of umpire signal in order to automate scoring system of cricket.

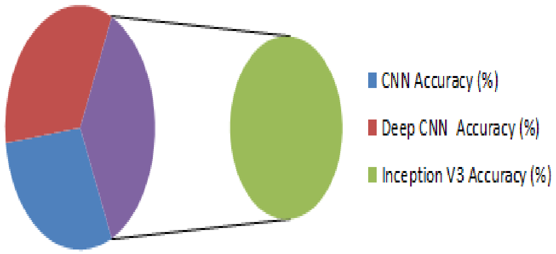

Fig. 6. Performance of single detection of umpire

IX. EXPERIMENTAL TOOLS

The whole task is performed Anaconda open-source Anaconda Distribution of python. For the implication of proposed DCNN, CNN, and Inception V3, we have applied TensorFlow and Keras. TensorFlow is an open-source software module that contained in Python for the dataflow and differentiable programming across a limit of works. It provides the symbolic math library and applied for machine learning and deep learning like a neural network. Keras is an open source software module for neural network contained in Python. It is susceptible of performing on top of the TensorFlow. Developed to be fast experimentation with deep neural networks, it is really amazing and extensible to use.

X. FUTURE WORK

In our propounded technique to classify third umpire decision and automate a scoring system that classifies umpire signal in a cricket match, we have shown a successful exerted of convolution neural networks, deep convolution neural network and inception v3 model from our image datasets without being used any sensors in the field cricket. Our procedure can be applied to classify another kind of decisions making not only for cricket but also other games like football, basketball etc. In future, we want to build an automated umpiring system based on computer vision application and artificial intelligence.

XI. CONCLUSION

In this paper, we determine the probability of third umpire decision and umpire signal classification applying softmax. Training a CNN using pre-trained Inception-V3 has showed a great outcome to separate cricket images for proposed tasks. We have exerted seven types of image datasets to train our system and re-trained Inception-V3's final layer. Then we have tested the re-trained model imparting an image which imparts the probability of the probable decisions. We exerted the cross-validation procedure in this system and improve our trained system that aided to obtain the performance more than expectation. Corresponding to many no ball detection approaches and applications, our approach is more effective and efficient.

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