Crick-net: A Convolutional Neural Network based Classification Approach for Detecting Waist High No Balls in Cricket

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Abstract. Cricket is undoubtedly one of the most popular games in this modern era. As human beings are prone to error, there remains a constant need for automated analysis and decision making of different events in this game. Simultaneously, with advent and advances in Artificial Intelligence and Computer Vision, application of these two in different domains has become an emerging trend. Applying several computer vision techniques in analyzing different Cricket events and automatically coming into decisions has become popular in recent days. In this paper, we have deployed a CNN based classification method with Inception V3 in order to automatically detect and differentiate waist high no balls with fair balls. Our approach achieves an overall average accuracy of 88% with a fairly low cross-entropy value.

Keywords: Inception V3, Cricket, Waist High No Ball, Convolutional Neural Network

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1 Introduction

Cricket is a worldwide popular game where a single delivery can change the fate of the game. Every delivery is counted as a crucial moment for both teams. Umpires make the decisions regarding a no ball. Different technologies are being used to help the umpires to take their decisions. But often due to human perception, deciding whether a bowled delivery is a no ball or legal ball makes controversies. So, it is very important to make an accurate decision regarding a no ball.

One of the most common reason is a waist-high full toss. A full toss is a delivery that reaches to the batsman without bouncing on the pitch first. However, a waist-high full toss is permissible from a slower bowler as long as it does not go above the batsman’s shoulder. If it does, then the umpire calls it a no ball. Television replays are being used to make the examination of this kind of delivery. So, umpires make their decision on their perception. But their perception cannot be accurate at all time as they are human. Besides, it is not always possible to make the accurate judgment regarding a no-ball using existing technologies. As a result, some doubts are created and the benefit goes to the batting team.

In cricket, it is challenging to develop such technology that can able to decide the waist-high no-ball in real time with higher accuracy. But in our research, we used a pertained model inception- v3 that uses different convolutional neural network`s layer to give a high degree of accuracy on the decision. Our proposed method is expected to perform better and low cost in operating due to no infield sensor and other devices. As umpires are responsible for deciding a no-ball so, many scenarios are created when a delivery is disapproved by umpires and some scenarios are declared a no-ball. As a consequence of no-ball, opposite team gets an extra run and delivery and also the batsman will not be given out except running out. Sometimes the umpire's decision makes controversies as they make a decision using television replays. In our system, we tried to end all these controversies and make a good result. Our goal is to measure the probability of an image either it is a no-ball or not, to make the automated umpiring system and to eliminate the shortcoming of human perception.

2 Background Study

2.1 Transfer Learning

Transfer learning uses the knowledge gained from solving one problem and apply it to another related problem. Facing the problem of collecting enough training data to rebuild models, transfer learning aims to transfer knowledge from a large dataset known as source domain to a smaller dataset named target domain. Either the feature spaces between domain data are different or the source tasks and the target tasks focus on different topics, boosting the performance of the target task. Transfer learning using CNN's is commonly used in different fields.

2.2 Inception-V3

Inception-v3 is a deep neural network which is very difficult to train it directly with a low configured computer. Using transfer learning sensor flow provides tutorials for us to retrain Inception’s final layer new categories. Transfer learning method keeps the parameters of the previous layer and remove the last of the Inception-v3 model and then retrain the last layer. The number of categories in the dataset is equal to the number of output nodes in the last layer just like ImageNet dataset which has 1000 classes, so the last layer has 1000 output nodes in the original Inception-v3 model.

2.3 Convolutional Neural Network

Convolution layer extract feature from an input image[4]. A convolutional operation is performed to the input and then passes the result to the next layer. Using small squares of input data, convolution learns image features and preserves the spatial relationship between pixels. CONV layer’s parameters are made of a set of learnable filters. Every filter is small spatially (along width and height), but extends through the full depth of the input volume.

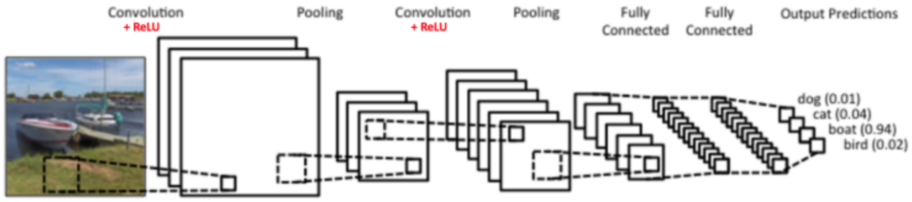

Fig 1. Convolutional Neural Network

Rectified linear unit or ReLU is the activation function which is commonly used in deep learning networks for hidden layers[4]. The function returns 0 if the input is less than 0 and if the input is greater than 0 then the output is equal to the input. Its derivative is either 0 or 1. When the input is positive the derivate is just 1 so there is no squeezing effect on back propagated errors. It can be written as,

$$f(x) = \max(0, x)$$

Where x is the input to a neuron.

Pooling or down sampling reduces the dimensionality of each sub-region but saves the most significant information[4,14]. Pooling layer is inserted in-between every consecutive Conv. layers in convolutional neural network architecture. Max pooling is generally used to reduce the dimensionality and get the highest element of each sub-region. Max pooling uses the maximum value from each sub-region of every node at the previous layer. Max pooling discards 75% of the activations and controlling overfitting.

Fully Connected layers are not defined by the number of nodes, just by how they are connected to adjacent layer`s nodes[4,14]. The fully connected layer also introduced by Dense layers used in classification adding previous layer neurons to every neuron on the next layer.

Different types of function like Softmax activation function[14], SVM, and many others are used here for high-level reasoning in the neural network. Let us consider a classification model to classify with n classes. This model takes input datasets and an algorithm and produces a score of each class. The Softmax activation function converts from score to the probability between 0 to 1.the summation of all probabilities is 1.we used this function to the final layer of convolutional neural networks to classify the classes. This function is produced by multiple class from an input array. The probability distribution of Softmax function is:

$$\sigma(x_j) = \frac{e^{x_j}}{\sum_{j=1}^{n} e^{x_i}}$$

Where i=1, 2, 3 ….n and j=1, 2, 3 ….n

Cross-entropy loss, or log loss[4], measures the performance of a classification model whose output is a probability value between 0 and 1. Cross-entropy loss increases as the predicted probability diverge from the actual label. In our classification tasks to classify no-ball based on images of no-ball, a very common type of loss function to use is Cross Entropy loss. It is defined as

$$H\ (p, q) = E_p\ [-\log^q] = H\ (p) + D_{kl}\ (p||q)$$

Where H (p) is the entropy of p. $D_{kl}\ (p||q)$ is the Kullback-Leibler divergence of q from p.

3 Literature Review

AZM Ehtesham Chowdhury, Md Shamsur Rahim, and Md Asif Ur Rahman proposed a method to detect foot overstep no-ball using computer vision where the bowling crease is divided into two regions and image subtraction method is applied to find the change in pixel values for both regions and get 100% accuracy [1].

Another cricket shot classification introduced using batsman's motion vectors by D Karmaker, AZM E Chowdhury, M S U Miah, M A Imran and M H Rahman. For action recognition, they use 3D MACH to classify the shots and to detect cricket shots they define 8 classes of angle ranges[2].

Another cricket shot classification using computer vision proposed by AZM Ehtesham Chowdhury and Abu Umair Jihan divided the approach into four phases of identifying batsman's hand stroke direction, tracking, detection of a collision of bat and ball and detection of human pose and skeleton joints[3].

Kalpit Dixit and Anusha Balakrishnan compare the performance of three different Convolutional Neural Networks to classify ball-by-ball outcomes for sports videos. They use a pre-trained VGG16 Net to classify each ball into four different outcomes and the prediction accuracy is 80%[4].

In another research paper, Nikhil Batra, Harsh Gupta, Nakul Yadav, Anshika Gupta and Amita Yadav proposed a multi-valued automated decision whether a ball is no-ball or wide ball[5]. Presenting game specific concept selection and event selection criteria

Maheshkumar H. Kolekar and Somnath Sengupta proposed a degree of abstraction parameter that extracts highlights automatically from a recorded video[6].

M.H. Kolekar and K. Palaniappan form a semantic video analysis based on low-level image features and high-level knowledge for cricket video sequences encoded in hierarchical classification[7].

In [8-16], different approaches of moving object detection, and sports analysis works has been shown.

4 Methodology

Workflow diagram of our methodology is given below -

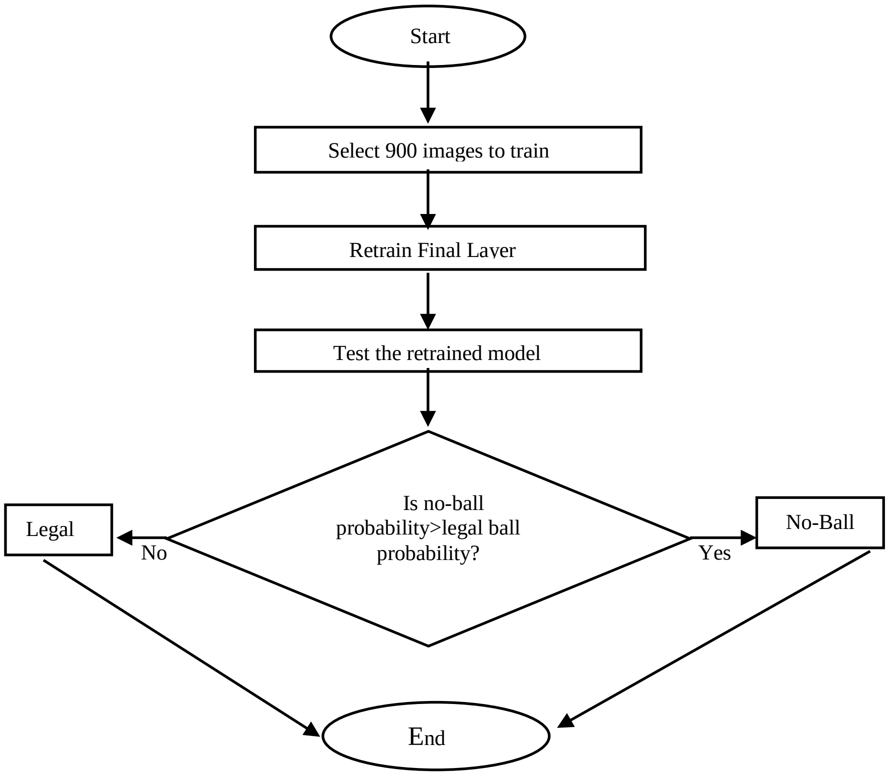

Fig 2. Workflow diagram

Our workflow is shown in Fig 2.

4.1 Data Collection Procedure

In our model to classify no-ball, we use images as input. Our input dataset contains 1000 images (sample shown in Fig 3). The images contain two classes: no-ball which has 500 images and legal ball which has 500 images. The images have different dimensions which are created by using Adobe Photoshop. We used Docker to build run the model, train it and test its performance. Our model produces a score for both of the possible outcomes then each of them is converted to a probability by softmax.

4.2 Data Preprocessing

All of our collected image data were resized in uniform size.

Fig 3. Our Dataset

4.3 Proposed Methodology

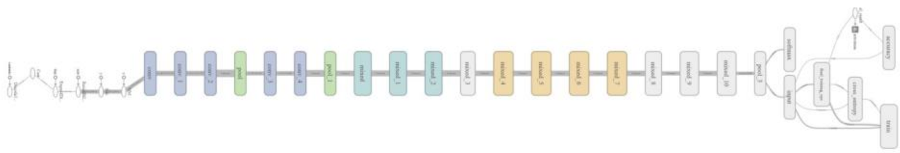

Fig 4. Our Retrained Inception V3 Model

We have used Inception V3 as the classifying CNN as our model (Fig 4). In this step, we should keep the parameters of the previous layer, then remove the final layer and input our dataset to retrain the new last layer. The last layer of the model is trained by back propagation algorithm, and the cross-entropy cost function is used to synthesize the weight parameter by calculating the error between the output of the softmax layer and the label vector of the given test category.

We also did 10-Fold Cross Validation and performed retraining of the final layer with our 900 training images. Detailed outcome of the cross validation is discussed in the result discussion section.

5 Result and Discussion

To measure the performance of our proposed system we use 100 images as test data in ten different datasets to test the accuracy. Our dataset contains 900 images. We applied Cross Validation Technique and portioned our final dataset into 10 equal subsamples to get a higher accuracy.

Result of our whole simulation is shown in Table 1. We used 100 images as test set each time for cross-validation. We have got the final average accuracy of 88% which is a fairly good one. It indicates high number of True Positives and lower number of False Positives and False Negatives.

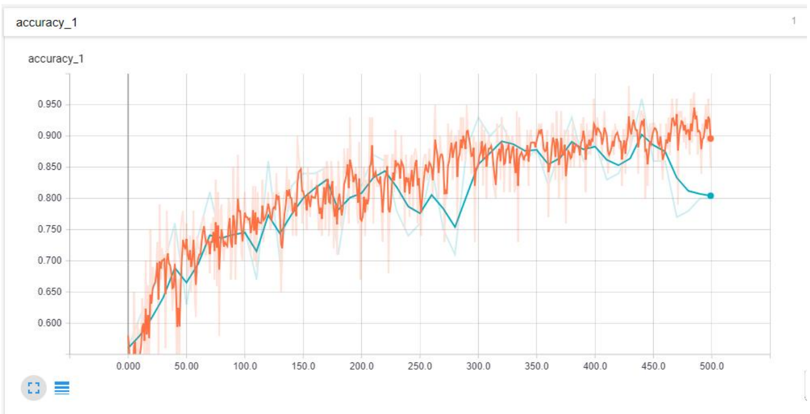

Fig 5. Training accuracy

From, Fig 5 we can see that, while training the data, we got the highest training accuracy of 94% while the highest validation accuracy achieved is 90%. It is noteworthy that this data was acquired from the 9th epoch of the Cross Validation which performed the highest.

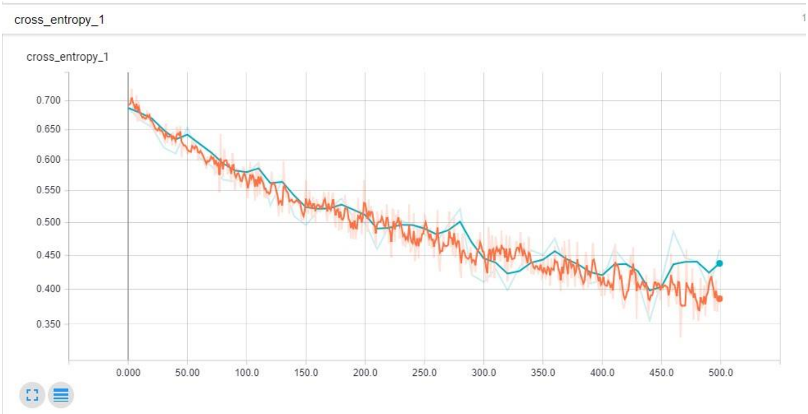

Fig 6. Cross-entropy of our model

From Fig 6, we can infer that, our cross-entropy for training set declined to the point as low as 0.37 the cross-entropy for validation set declined to the point as low as 0.35 which is moderately fair. From both of the above presented figures, we can also infer that, the dataset had a lot of random noises or distortions which caused the sudden spikes in the training accuracy graphs. This is due to the synthetic nature of the used dataset which was error-prone.

Table1. Measure Accuracy based on confusion matrix.

Number of iteration	Recall (%)	False positive rate (%)	Specificity (%)	Precision (%)	F - measure (%)	Accuracy on Test Data (%)
1	82	11	88	90	86	85
2	82	11	89	90	86	85
3	86	13	87	88	86	86
4	80	03	97	98	88	87
5	80	03	97	98	88	87
6	84	09	91	92	88	87
7	93	15	85	84	88	89
8	83	0	100	100	91	90
9	94	11	89	88	91	91
10	90	06	94	94	92	92

Table 1 contains precision, recall, Specificity, False Positive Rate, f-measure, and accuracy of the model. Also, the Macro Average of our Precision, Recall, Accuracy and F-Measure values are shown in Fig 7. From this, we can see that our model has achieved a pretty good Precision, Recall, Accuracy and F-Measure value with very low False Positive Rate (FPR).

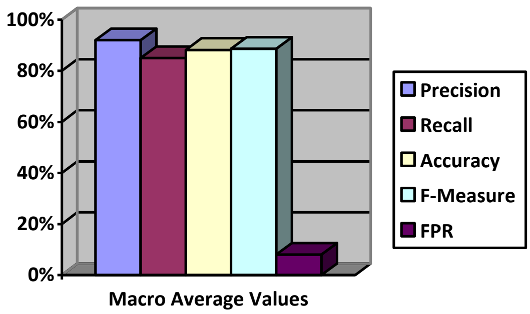

Fig 7. Macro Average Values

6 Future Works

In our proposed method to detect waist high full toss no-ball in a cricket match, we have used convolution neural networks to build a model from our image dataset without using any sensors in a field. Our system can be used to detect others type of no-ball corresponding to waist high full toss no-ball and leg before wicket(lbw) detection and wide ball detection. In future, we want to develop an automated umpiring system based on computer vision application.

7 Conclusion

In this paper, we measure the probability of an image either it is a no-ball or not using softmax. Training a Convolutional Neural Network using pre-trained Inception-V3 can show great outcome to classify cricket images. We use 900 images to train our model and retrained Inception-V3's final layer. Then we test the retrained model using an image which gives the probability of no ball or legal ball. We used the cross-validation technique in this model and get the accuracy of 88% which is more than expectation. Using this model we eliminated the shortcoming of Umpire's perception to decide a waist-high full toss no-ball. Corresponding to many no ball detection approaches and applications, our approach is more effective and efficient.

8 References

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