WAIST-HIGH FULL TOSS NO-BALL DETECTION USING DEEP NEURAL NETWORK

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9th July, 2020

APPROVAL

This Research titled **"Waist-High Full Toss No-Ball Detection using DeepNeural Network"**, submitted by **MD. SALAH UDDIN** to the Department of Computer Science & Engineering, **Daffodil International University**, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc in Computer Science & Engineering and approved as to its style and contents. The presentation has been held on 9th July, 2020.

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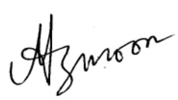

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DECLARATION

I hereby declare that this research has been done by me under the supervision of **Mr. Md. Sadekur Rahman** Assistant Professor and co-supervision of **Mr. Md. Riazur Rahman ,** Sr. Lecturer, Department of CSE, Daffodil International University. I also declare that neither this research nor any part of this research has been submitted elsewhere for the award of any degree.

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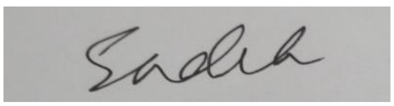

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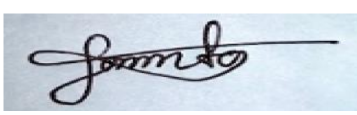

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ACKNOLEDGEMENT

First I express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the eventual year project/internship successfully.

At first, I’d like to thank my respected **Supervisor**, **Mr. Md. Sadekur Rahman ,** **Assistant Professor and Co-Supervisor, Mr. Md. Riazur Rahman , Sr .Lecturer**, Department of Computer Science & Engineering, Daffodil International University . This whole time they have supported me, inspired me and showed me the right way. They made it easier for me to work continuously with all their patience and inspirations. Every time I had a difficulty, I contacted them and they helped me with a suggestion and that helped me a lot throughout the whole time.

I would like to express our heartiest gratitude to **Professor Dr. Syed Akhter Hossain**, Head**,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

Eventually, I must acwisdom with due respect the constant support and patients of our parents.

ABSTRACT

Cricket is a popular freak all over the world where several technologies are being leaded to aid the match umpires to make decisions, often due to the human savvy , composing whether a bowled allotment is a no-ball or juridical ball which can leads dispute . As only a single ball execute switch the lot of the game, so it is obvious to make an proper decision regarding no ball. This is the most commonly reasons is waist-high of the batsman and the height of the ball upon the stamp. But the examination of this kind of No Ball requires some minutes in certain cases using television replay . So umpires give their decisions on their savvy. But human savvy cannot be proper all the time. Besides, it is not always possible to cease the proper judgment becalead of the limitations of existing technology. In that case, the favor of the doubt goes to the batting team. And this creates mass bewilderment and debates among the viewers and cricket lovers. In this project, we award our array task as the prediction of the delivered ball is a no-ball or juridical ball .

This system gives the probability of juridical ball and no-ball measuring the height of the waist. Our refuge eliminates the shortcomings of human savvy to detect waist-high no-ball.

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CHAPTER 1
Introduction

1.1 Introduction

Cricket is a game of bat and ball where a single allotment can dice the expectant conqueror into a loser. So, every allotment is counted as a crucial moment for both teams. There are two teams in a cricket match and they are play with each other on the play ground and they fighting with each other and each team has 11 players And in the middle there have a pitch and it's width is 22 yard and in this pitch they are playing bat or bowling . In this two team one team is decide to take bating and another decide to bowling after the toss and bating team is trying to make a good run . And the opponent team try to do good bowling and they want to kick out the bats man . After one bats the bowling team going to do batting and trying do most run .In this total we are calling an innings . If they want to a winning mach one have to do their most run if they make most run they will win . In this total innings three umpires was working , two umpires is in the field and third umpire was helping the two umpire .

1.2 Motivation

In each cricket match, Umpires are liable for scrawl the approval of a ball bowled by a bowler. There are many scenarios when a allotment is disapproved by umpires. Some of the scenarios are declared as No Ball. A No Ball can be declared for ilajuridical acts by bowlers or fielders. As a consequence of a No Ball, the opposing team gets an extra run and allotment. Furthermore, the batsman will not be given out except running out. Sometimes the decision of the umpire gets controversial as they take their decision using television replay which is also time-consuming. My system helps me to finish many of these debate and gives a well result.

1.3 Research Questions

1. Is it always proper to decide a no-ball by umpire's perception?

1.4 Expected Outcome

- Detect an image and give result is it a no-ball or not.
- Can be an automated umpiring method .
- To sort out the blame of human savvy .

1.5 Layout of the Report

Chapter one have demonstrated an introduction to the project with its motivation, research questions, and expected outcome.

- Chapter two will have "Background" demonstrates introduction, related works, research summary, and challenges.
- Chapter three will have Research Methodology.
- Chapter four will have Experimental Results and Discussion.
- Chapter five will have Summary and Conclusion.

CHAPTER 2
Background Study

2.1 Introduction

In this section, we will discuss related works, research summary and challenges about this research. In related works section, we will discuss other research paper and their works, their methods, and accuracy which are related to our work. In research summary section we will give the summary of our related works. In challenges section, we will discuss how we increased the accuracy level.

2.2 Related Works

A.Z.M. Ehtesham , Md Shamsur Rahim, and Md Asif Rahman moved a system to dig up limp excel no-ball treat computer glance where the bowling crease is separated into two part and icon deduction system is pratical to get the switch in pixel grade for both part and get 100% accuracy [1]. Another cricket shot array moved using batsman's pace vectors by D Karmaker, AZM E Chowdhury, M S U Miah, M A Imran and M H Rahman. For act confession, they lead 3D MACH to categorize the shots and to detect cricket shots they award 8 classes of angle ranges[2]. Another cricket shot array using computer vision moved by AZM Ehtesham Chowdhury and Abu Umair Jihan divided the refuge into four phases of identifying batsman's hand stroke direction, tracking, detection of a jog of bat and ball and detection of human spasm and skeleton joints[3]. Kalpit Dixit and Anusha Balakrishnan analogy the performance of three several Convolutional Neural Networks to categorize ball-by-ball outcomes for sports videos. They lead a pre-trained VGG16Net to categorize each ball into four several outcomes and the prediction accuracy is 80%[4]. In another research paper, Nikhil Batra, Harsh Gupta, Nakul Yadav, Anshika Gupta and Amita Yadav moved a multi-valued automated decision whether a ball is no-ball or wide ball[5] .

2.3 Research Summary

Table 2.1:Research Summary

SL	Author	Methodology	Description	Accuray
1.	A.Z.M. Ehtesham Chowdhury, Md Shamsur Rahim, and Md Asif Ur Rahman	Image subtract method	Detection of foot overstep no-ball	100%
2.	D karmakar, AZM E Chowdhury, M S U Miah, M A Imran and M H Rahman	3D MACH(maximum average correlation height Filter), Pace vector	Awards 8 classes of angle ranges to detect cricket shots which is grounded on Pace vectors that help to measure the angle of any precise cricket shot.	SquareCut- 61.22%, Hook- 53.32%, Flick- 62.74% Off Drive- 63.57%
3.	A.Z.M. Ehtesham Chowdhury	Scale-invariant refuge	Extracting salient feature and optical flow from videos of cricket shots	Classified cricket shots
4.	Kalpit Dixit and Anusha Balakrishnan	VGG16Net, Softmax Function, Cross-Entropy Loss, Transfer Learning Fine tuning and learning layers from scratch, Single Frame Array,	Categorize outcomes from cricket videos and explore three several deep learning architectures to output a array of the input ball video into one of four classes: {“no run”, “runs”,	80%

		LSTMs, Late Fusion	"boundary", "wicket"}.	
5.	Nikhila Batra, Harshan Gupta, Nakul Yadave, Anshika Gupta	Canny Edge Detector, Hough's Line Transform, Dougls Peucker Algorithm.	Implements two of the most important requirements of the game, that are- Approximating the trajectory of the ball and Automating wide ball Decision Making.	Augmented reality in cricket and automated no ball decision.
6.	Maheshkumar H. Kolekar and Somnath Sengupta	Highlight Generation Algorithm	Extract highlights from recorded video of cricket match	Highlights are extracted.
7.	M.H. Kolekar and K. Palaniappan	Hierarchical array	Performs a topdown video event detection and array using hierarchical tree which avoids shot detection and clustering	Detect semantic event and classified cricket videos.

2.4 Challenges

The accuracy of detecting no-ball was not high. I tried to increase the accuracy of no-ball detection by using traditional machine learning like transfer learning, convolutional neural network, Inception-V3 etc.

CHAPTER 3

Research Methodology

3.1 Data Collection Procedure

In my norm to rate no-ball, I lead images as input. My input dataset hold 1000 images[16] from which I lead 900 images to train the norm and another 100 images to experiment the norm . The test images take on two classes: no-ball which has 450 images and juridical ball which has 450 images. The images have several dimensions which are tooled by using AdobePhotoshop. I lead docker to build run the norm, train it and experiment its performance. My norm generate ascore for both of the possible outcomes then each of them is converted to a odds by softmax. The dimensions of images is:

Table 3.1: Dimension of images

Number of pictures	Dimensions
490	322×326
85	277×239
76	360×269
66	617×444
64	322×340
64	723×371
53	831×554
52	846×720
50	688×675

3.2 Analysis of Dataset

I select nine hundred pictures to train and retrain Inception-V3's eventual layer. Then I experiment the retrained norm. I experiment the norm with 100 images and check each image if it is a no-ball or juridical ball.

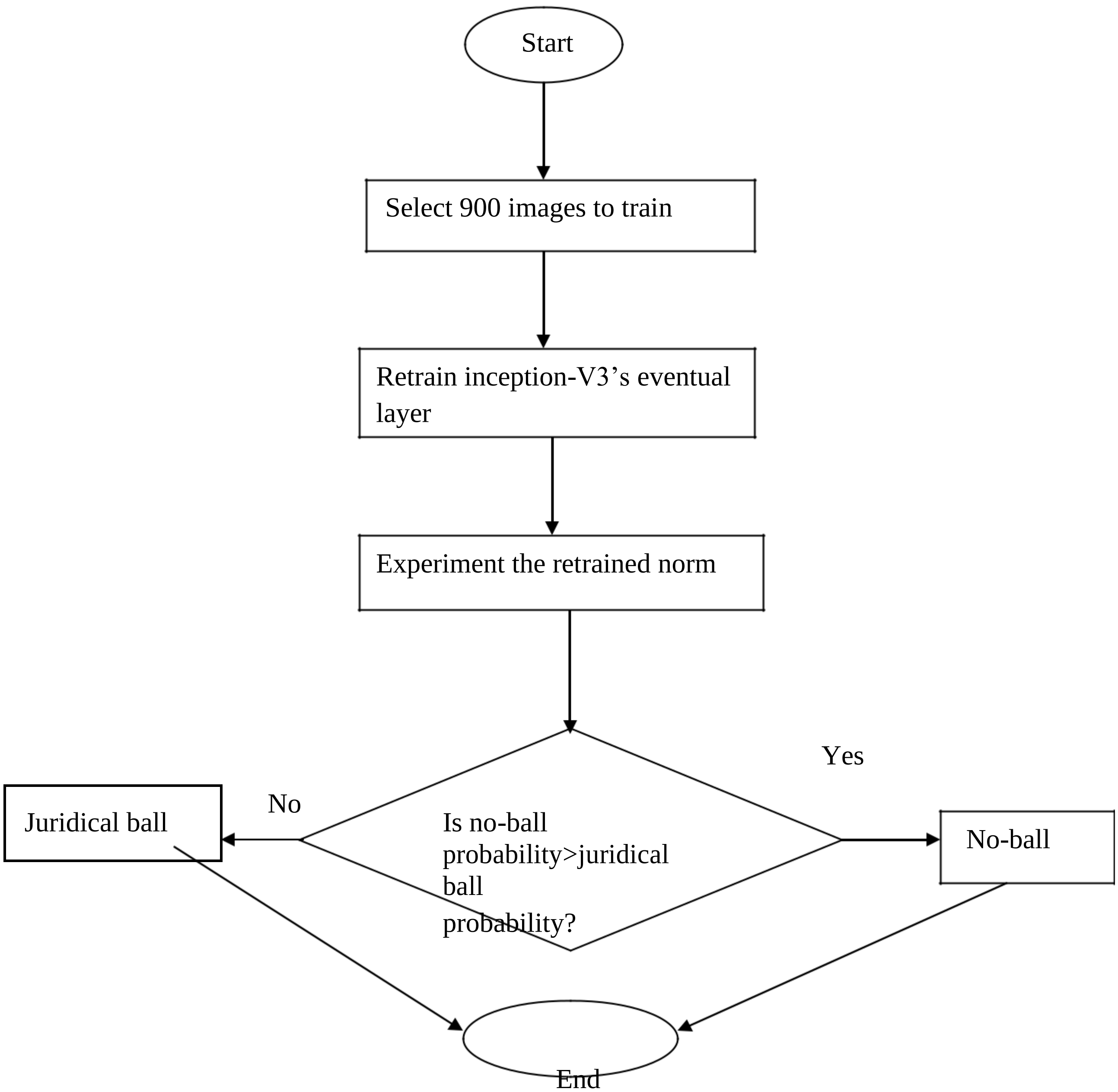

Figure. 3.1: Flow Chart of Moved Norm

3.2.1 Inception-V3

Inception-V3 is a norm which is trained to categorize an image with an error rate that moved human performance. An important trick factorization is moved in Inception-V3 which factorizes big kernels into small kernels such as one 7x7 kernel= two 5x5 kernels with strides 2 = three 3x3 kernels with stride 1.

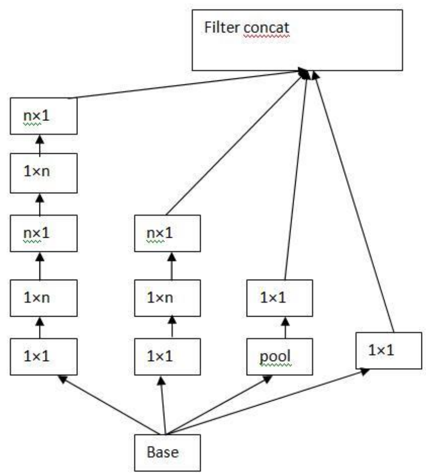

Figure:3.2: Inception module after the factorization the n×n convolutions.

In above picture, after factorizing n * n into 1 * n and n * 1, the inception module was chosen n=7. A 17x17 grid looks like this:

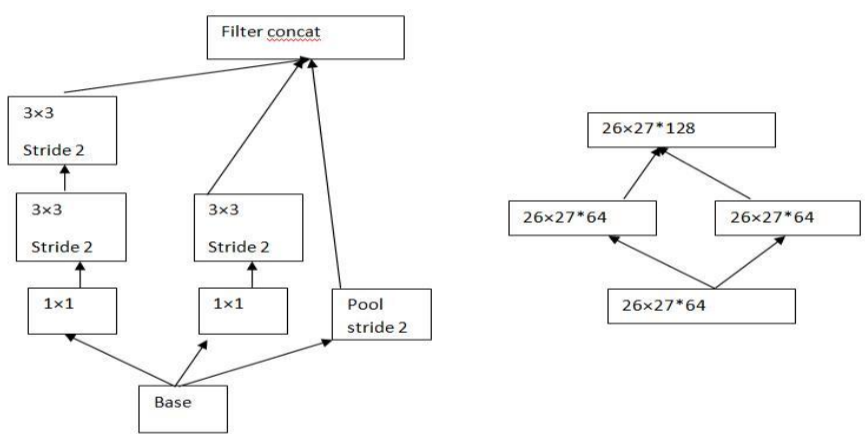

Figure:3.3: Inception module that reduce the grid size while expands the filter banks.

In this figure inception module reduces the grid size and expands the filter banks which is at the same time cheap and avoids representational bottle necks .We lead Inception-V3 to extract the feature from our input image using our CNN norm and then categorize both juridical and no-ball part by using fully-linked layer and softmax layer.

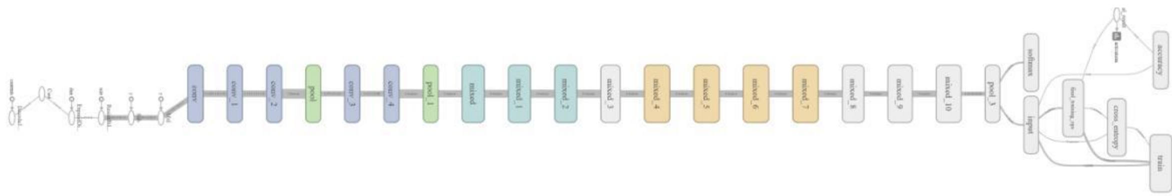

Figure 3.4: Eventual architecture of inception v3

3.2.2 Transfer Learning

Transfer learning leads the wisdom gained from evolve one puzzle and apply it to another related puzzle. Three major scenarios of transfer learning are, ConvNet as fixed feature extractor, whereby taking a ConvNet pre-trained on ImageNet the last fully-linked layer is removed and the rest of the ConvNet is treated as a fixed feature extractor for the new dataset. The second one is Fine-tuning the ConvNet, leadd to fine-tune the weights of the pre-trained network by continuing the backpropagation. it’s possible to keep some of the earlier layers fixed and only fine-tune some higher-level portion of the network or to fine-tune all the layers of the ConvNet. In pre-trainednorms, the network is trained on large dataset like ImageNet and also trained all the parameters of the neural network and it takes hours on GPU. We lead the pre-trained Inception-V3 for our analysis by loading all layers of the Inception-V3 with pre-trained weights. We leadd to transfer learning to retrain our dataset which is several from Inception-V3 images.

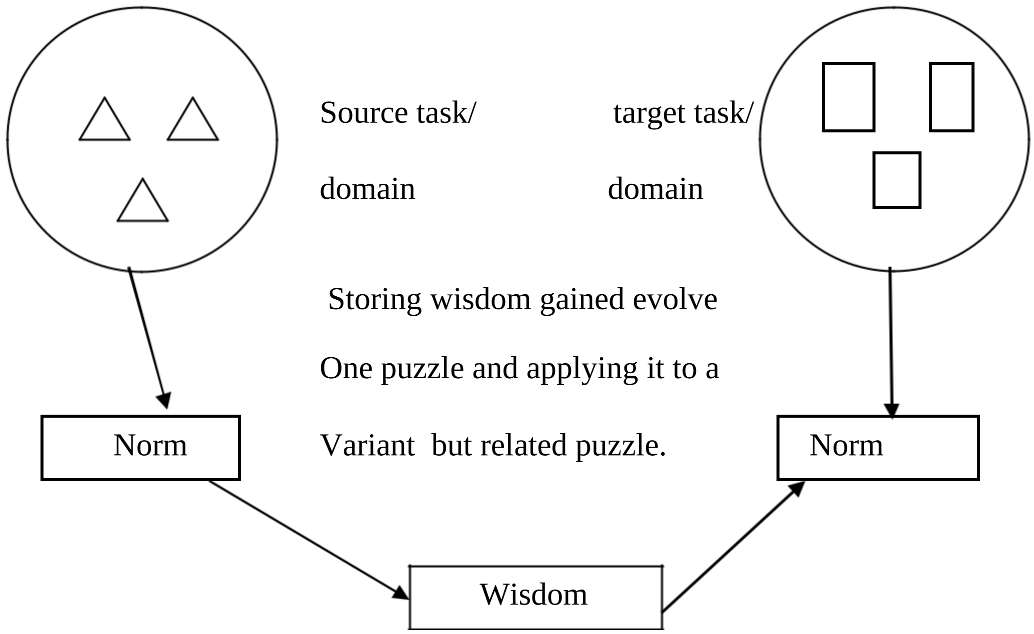

Figure 3.5: Transfer Learning

3.2.3 Convolutional layer :

Convulsion level extraction feature from an input figure. A convoluted operation is accomplished at the input and then the result passes to the up comming level. Using small squares of input data, the convolution become the properties of the image and conserve the local relationship between the pixels. The parameters of the CONV layer are tooled by a set of learnable filters. Each filter is spatially small (along the width and height), but enlarge through the full depth of the input volume. An example of the level of convolution:

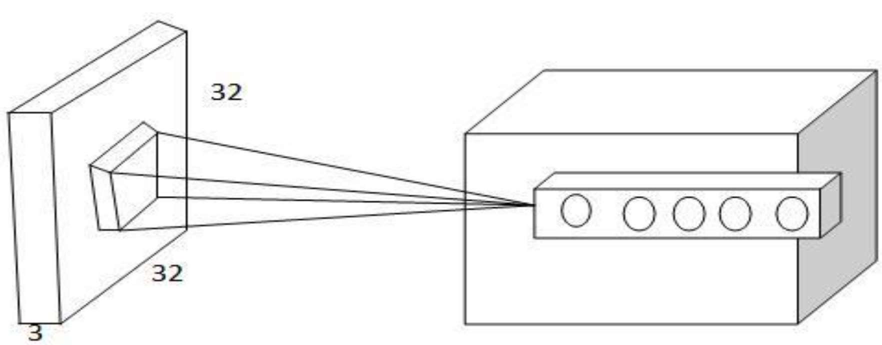

Figure: 3.6:Convolutional layer

This is the red input volume (e.g. a 32x32x3 CIFAR-10 figure) and the example volume of the neuron at the first convoluted level. At the conventional level each neuron is only spatially linked to a local region of the input volume, but deeply there are multiple neurons (5 in this example) all looking at the same region at the input.

3.2.4 Rectified linear unit (ReLU)

Rectified linear unit or ReLU is the activation function which is usually lead in deep learning networks for covert layers. The function returns 0 if the input is less than 0 and if the input is massive 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,

3.2.5 Max pooling

The most common form of pooling is max pooling. Max pooling is done to in part to help over-fitting by providing an abstracted form of the representation. As well, it reduces the computational cost by reducing the number of parameters to learn and provides basic translation invariance to the internal representation.

3.2.6 Fully Linked Layer

Fully Linked layers are not awardd by the number of nodes, just by how they are linked to adjacent layer`s nodes. The fullyLinked layer also moved by Dense layers leadd in array adding previous layer neurons to every neuron on the next layer. Several types of function like softmax activation function, SVM, and many others are leadd here for high-level reasoning in the neural network. But in our norm, we stick leadd softmax for array. After several convolution and pooling layers, we get some high-level features as input. These input images features are leadd as categorizeing to explore various classes. But when we combine convolution layer`s features and polling layer`s features it gives the better result of arrays. In Fully Linked layers summation of output probabilities is 1.One Conv layer share weights with other Conv layers.It is very difficult to attach all nodes with a softmax layer that’s why we lead a fully-linked layer to increase the efficiency of array in our norm.

3.2.7 Softmax

Let me consider a array norm to categorize with n classes. This norm takes input datasets and an algorithm and generate a score of each class.the softmax promptness act proselyte from score to between 0 to 1.the summation of all probabilities is
1.I leadd this function to the eventual layer of convolutional neural networks to categorize the classes .This function is produced multiple class from an input array.the probability format of softmax function is:

$$(i) = \frac{}{\sum_{j=1}}$$

Where i=1,2,3,…….n and j=1,2,3,…….n

3.2.8 Cross Entropy

Cross-entropy loss, or log loss, extent the redaction of a array norm whose output is a probability honor between 0 and 1. Cross-entropy loss enhancement as the enumerated probability diverge from the actual label. In our array tasks to categorize no-ball based on images of no-ball, a very same type of loss function to lead is Cross Entropy loss. It is awarded as

$$(P) = p\ q\ [-\log] = \ (P) + \ (q)$$

Where H(p) is the entropy of p is the kullback-leibler divergence of q from p.

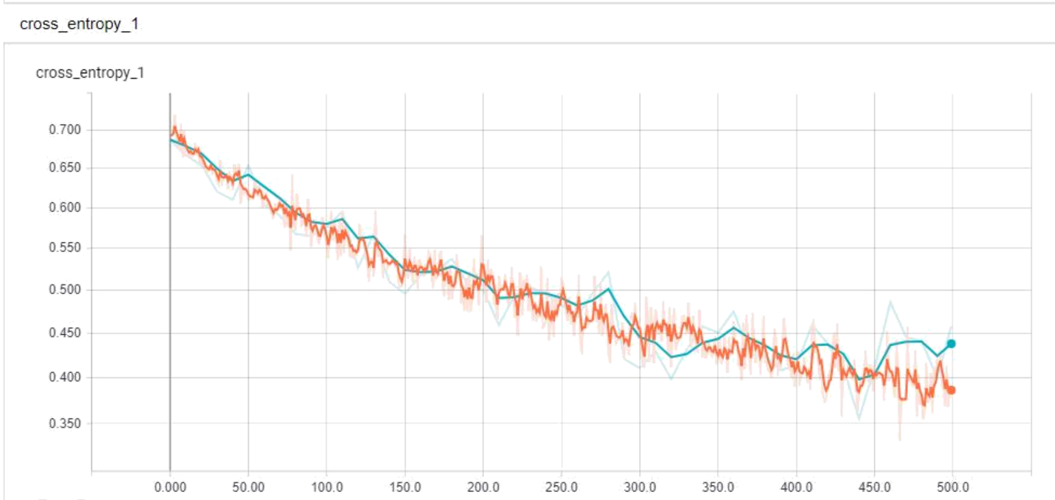

Figure3.7:cross entropy error function

3.3 Moved Methodology

In my moved method i lead the convolutional neural network.i lead four type key type of layers to set up my architecture: convolution layer, ReLu layer,max-pooling and fully linked layer and lead softmax function to categorize the probability of all the outputs.

I measure the dimension from the previous activation in each convolution layer by the following equation is given by

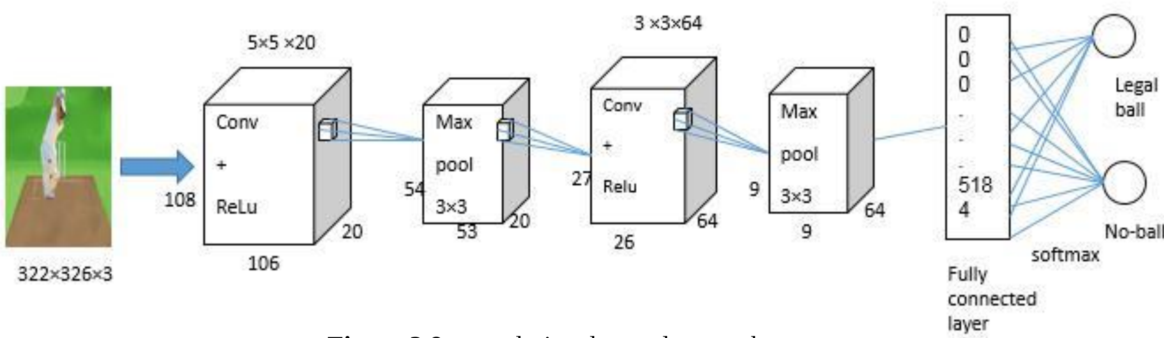

Figure 3.8:convolutional neural network

Our norm take input as raw pixels value of the image with dimension 322×326×3.the dimension is described as width:322, height:326 and the number of channels are 3.channel 3 means it take ons the color of Red, Green, and Blue.

we apply 5×5 convolution layer and ReLu with padding p=0and stride s=3 for out input image to compute the output of neurons. This layer is multiplied by the input image and we decided to lead 20 filters.apply the 5×5 convolution layer to get the neurons as output is 106×108×20.

For this output, we apply 3×3 max pool with stride s=2 to compute the output of neurons. The output is 53×54×20. Both conv+Relu and max pool are represented layer one.

For the next step, we apply 3×3 c convolution layer+ ReLu with padding p=0 and stride s=2 and decided the number of filters is 64.again this layer is multiplied by the previous activation output and produce the output neurons is 26×27×64.

Again we apply 3×3 max pool with the stride s=2 and no of riddle is same as the previous convolution ledge .the output of the layer is 9×9×64.

ReLu layer is applied an elementwise activation function and the output volume is unchanged.

The fully linked layer is made by the all activations of in the previous ledge and computes the class score.the volume of the resulting size is 5184.

We apply softmax function in the fully linked layer to categorize the probability of all the outputs and output classes are no-ball nad juridical ball.

When we train and experiment our data in our norm its takes more time to train our datasets.the computational cost and hardware requirement is high.and the accuracy of our norm is 30%.

We want to increase the accuracy of our moved norm that’s why we lead inception v3 in the last layer in our norm.inception v3 is a pre-trained norm by GooLeNet.

We will describe a small portion of inception v3.the module take on a several type of convolution layer: 1×1,3×3,5×5 and 3×3 max pooling .

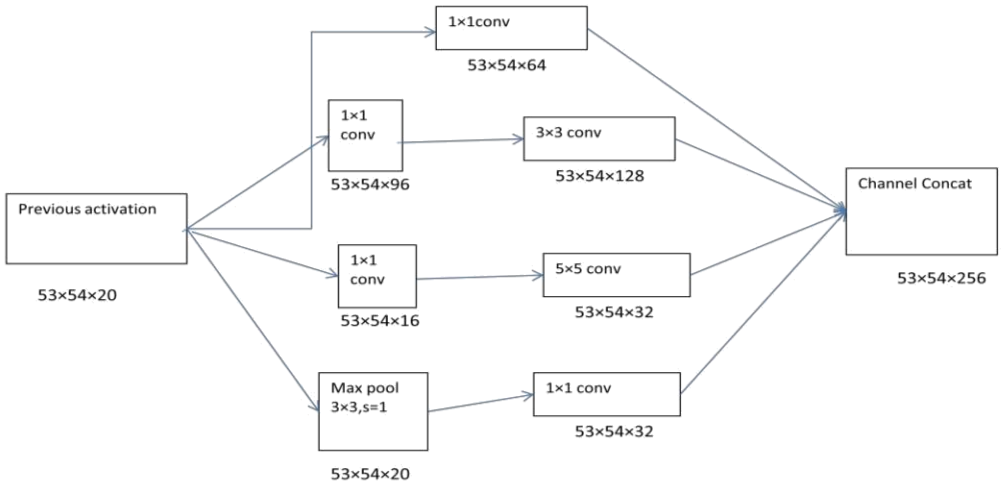

Figure 3.9: Inception-v3 module

out previous activations are 53×54×20.here width: 53, height:54 and number of channel is 20.apply 1×1 convolution with a number of channels 64 and padding p=0 and stride s=1.the output is 53×54×64.

Applying another 1×1 convolution followed by 5×5 convolution with padding p=2 and stride s=1 and number of channels 32.the output is 53×54×32.

Applying another 1×1 convolution followed by 3×3 convolution with padding p=1 and stride s=1 and number of channels 128.the output is 53×54×128.

Apply 3×3 max pooling with stride s = 1 followed by the 1×1 convolution with padding p=0 and stride s=1 and the output is 53×54×32. The channel concatenation is the summation of all the convolution layer and max pool layer is 53×54×256.

Applying inception v3 in our moved method to rise the exactitude . The exactitude of our moved method is 84%.

Chapter 4

Experimental Results and Discussion

4.1 Experimental Results

To measure the performance i use 900 image .I get the eventual accuracy 88% which is much higher than we expected. Using these 10 subsample accuracy values we draw a number of iteration versus accuracy graph. We also lead the binary confusion matrix to calculate precision, recall, Specificity, False Positive Rate, f-measure, and accuracy of the norm.

The confusion matrix is a table to describe the performance of a array norm on a set of experiment data. Confusion matrix can award four terms:

True Positive (TP): we predicted result as no-ball which are actually no-ball.

True Negative (TN): we predicted result as juridical which are actually juridical.

False Positive (FP): we predicted No-ball, but these are not actually no-ball.

False Negative (FN): we predicted juridical, but these are actually no-ball.

Recall: Recall is the piece of topical case that have been retrieved over the total amount of pertinent example . High recall cause that an algorithm come back most of the incidental result.

F-means: f-score is a measure of experiment's exactness by weigh both precision and recall. it is a tuneful average of precision and recall.

Accuracy: accuracy refers to the familiarity of the measured value to a known value.

False Positive Rate: False positive rate are refers that our moved method predict the ball is no-ball when it's actually juridical ball. Calculate the false positive rate by the given equation:

Equation:

$$precision = \frac{tp}{tp + fp}$$

$$Recall = \frac{tp}{tp+fn}$$

$$F - Score = 2 * \frac{precision*recall}{precision+recall}$$

$$specificity = \frac{tn}{tn + fp}$$

$$accuracy = \frac{tp + tn}{tp + tn + fp + fn}$$

$$False\ positive\ rate = \frac{fp}{tn + fp}$$

Specificity: Specificity refers that our moved method predict the ball is a juridical ball when it’s actually juridical ball. calculate the specificity of the given equation:

Table 4.1: Measure exactitude based on confusion matrix.

Number of iteration	Retraction (%)	False positive rate(%)	Specificity (%)	Precision (%)	F-measure (%)	Accuracy (%)
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
Average	85	08	92	92	88	88

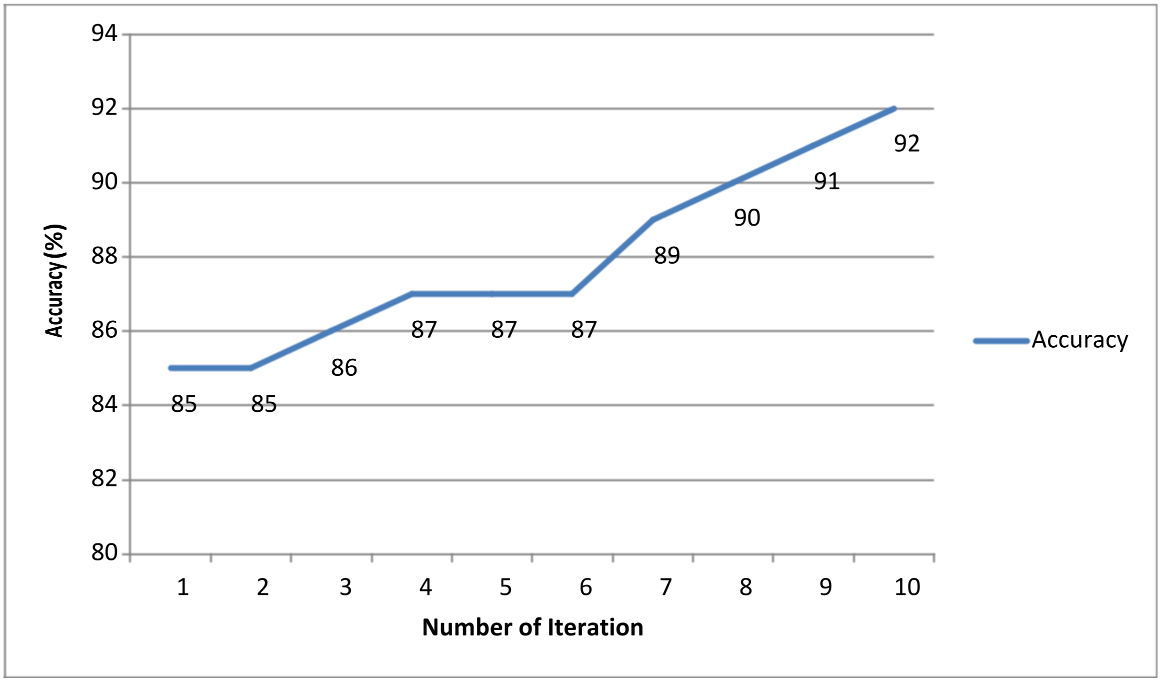

Figure 4.1: Number of iteration versus Accuracy

CHAPTER 5

Conclusion and Future works

5.1 Conclution

In this paper, I use any types of software like softmax , Convolution layer etc.And i aslo use the Inception model . I lead 900 images to train our norm and retrained Inception-V3's eventual layer . Then I experiment the retrained norm using an image which pay the probability of no ball or juridical ball. I conduct the cross validation method in this norm and get the accuracy of 88% which is more than expectation. Using this norm I eliminated the shortcoming of Umpire's perception to decide a waist-high full toss no-ball.

5.2 Future Works

In my moved method to detect waist high full toss no-ball in a cricket match, I have conduct convolution neural networks to build a norm from my image dataset without using any sensors in a field. I am trying to do 95% or more than this accuracy . I will continue my work and INSALLAH one day i will do 95% or more than accuracy .

REFERENCES

[1] AZME Chowdhury, M. S. Rahim and M. A. U. Rahman, "Application of computer vision in Cricket: Foot overstep no-ball detection," 2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, 2016, pp. 1-5.

[2] D. Karmaker, A. Z. M. E. Chowdhury, M. S. U. Miah, M. A. Imran and M. H. Rahman, "Cricket shot array using pace vector," 2015 Second International Conference on Computing Technology and Information Management (ICCTIM), Johor, 2015, pp. 125-129.

[3]Chowdhury, AZM Ehtesham and Abu Umair Jihan. “Array Of Cricket Shots Using Computer Vision.” (2014).

[4] Kalpit Dixit and Anusha Balakrishnan, Deep Learning using CNNs for Ball-by-Ball Outcome Array in Sports", report submission on the course of Convolutional Neural Networks for Visual Confession, Stanford University,2016.

[5] Batra, Nikhil & Gupta, Harsh &Yadav, Nakul& Gupta, Anshika&Yadav, Amita. (2014). Implementation of augmented reality in cricket for ball tracking and automated decision making for no ball. 316-321. 10.1109/ICACCI.2014.6968378.

[6] M. H. Kolekar and S. Sengupta, "Event -Importance Based Customized and Automatic Cricket Highlight Generation," 2006 IEEE International Conference on Multimedia and Expo, Toronto, Ont., 2006, pp. 1617-1620.

[7] M. H. Kolekar, K. Palaniappan and S. Sengupta, "Semantic Event Detection and Array in Cricket Video Sequence," 2008 Sixth Indian Conference on Computer Vision, Graphics & Image Processing, Bhubaneswar, 2008, pp. 382-389.

[8] R. Tandon, “Semantic Analysis of a Cricket Broadcast Video,” pp. 1–9, 2009. [Online]. Available:http://www.cse.iitk.ac.in/leadrs/rashish/EventualReport.pdf.

[9] D. S. Rughwani, “Shot Array and Semantic Query Processing on Broadcast Cricket Videos Shot Array and Semantic Query Processing on Broadcast Cricket Videos,” no. September, 2008.

[10] M. D. Rodriguez, J. A hmed, and M. Shah, “Act MACH A Spatiotemporal Maximum Average Correlation Height Filter for Act Reco gnition.”

[11] S. H. Zhang Z, “Skeleton body spasm tracking from efficient threedimensional pace estimation and volumetric reconstruction,” International Journal of Computer Science and . . . , 2013. [Online]. Available: http://www.opticsinfobase.org/abstract.cfm?uri=ao-51-23-5686 http:/ /ijcsmc.com /docs/ papers/ April2013/V2I4201376.pdf

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