Front Foot Overstep No ball Detection

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1 Introduction

In cricket, a no-ball is an illegal delivery to a batsman. If the bowler bowls without some part of the front foot behind the popping crease (either grounded or in the air) when it lands, it is called a no-ball. This project aims to detect whether a bowler delivery is a Legal or No-Ball delivery using the images of bowlers in action. The goal is to measure the probability of an image being a no-ball or not and to make an automated umpiring system, eliminating the shortcoming of human perception.

2 Dataset

In our model, we have used 5670 images of size 100 x 100 x 3 as input. Our input dataset contains images collected from google image search and various video clips from live matches. The images indicating no ball and legal delivery are shown below. The images are manually annotated and contains two classes:

- No ball - 1
- Legal ball - 0

Figure 1: No Ball, Legal Ball

3 Methodology

We have deployed a **Convolution Neural Network (CNN)** based classification method with **VGG19** to automatically detect and differentiate foot overstepping no balls from fair balls. We have used **transfer learning** algorithms which uses the knowledge gained from solving one problem and applying it to another related problem. Transfer learning aims to transfer knowledge from a large dataset known as source domain to a smaller dataset named target domain. We have used Keras and Tensorflow to build our model and generate results. Our model produces a score for both possible outcomes then each of them is converted to a probability by sigmoid activation function.

4 Model Architecture

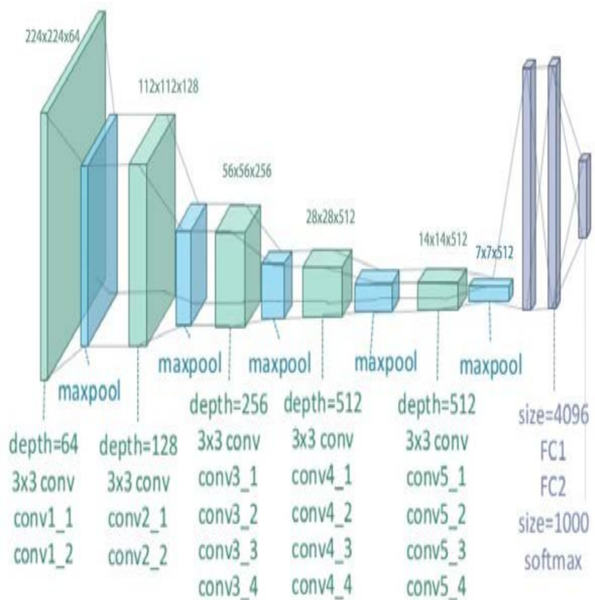

Figure 2: Model Architecture

5 Model Summary

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg19 (Functional)           (None, 3, 3, 512)         20024384
_________________________________________________________________
flatten (Flatten)            (None, 4608)              0
_________________________________________________________________
dense (Dense)                (None, 4096)              18878464
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 4097
=================================================================
Total params: 38,906,945
Trainable params: 18,882,561
Non-trainable params: 20,024,384
```

Figure 3: Model Summary

6 Hyper Parameters

Model Used	VGG 19
Number of hidden layers	20
Epochs	50
Optimizer	Adam
Metrics	Accuracy

Table 1: Hyper Parameter

7 Results

7.1 Metrics Used

TP (True Positive) denotes no balls predicted correctly,
TN (True Negative) denotes legal balls predicted correctly,
FP (False Positive) denotes legal balls predicted incorrectly,
FN (False Negative) denotes no balls predicted incorrectly.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

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

Training Accuracy	0.95
Test Accuracy	0.93
Precision	0.91
Recall	0.94
F1-Score	0.92

Table 2: Metrics

```
              precision    recall  f1-score   support

           0       0.95      0.93      0.94       653
           1       0.91      0.94      0.92       481

    accuracy                           0.93      1134
   macro avg       0.93      0.93      0.93      1134
weighted avg       0.93      0.93      0.93      1134
```

Figure 4: Classification Report

7.2 Performance

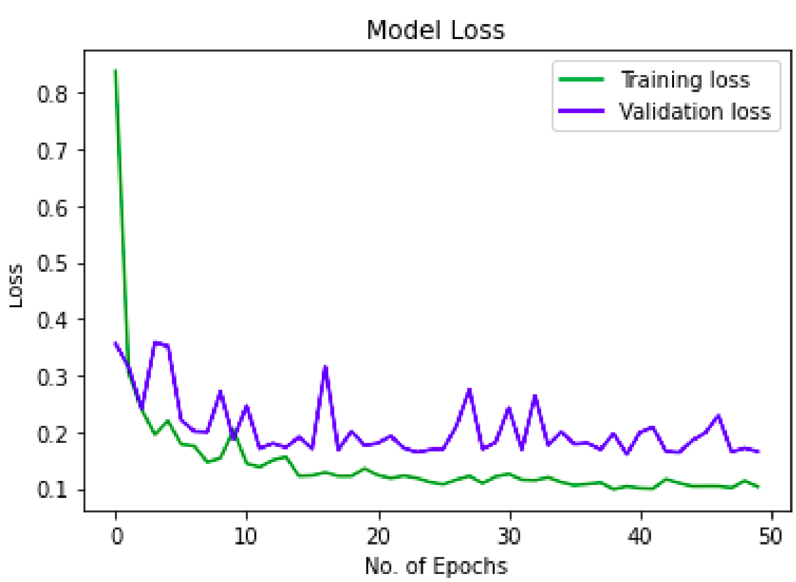

Figure 5: loss Plot

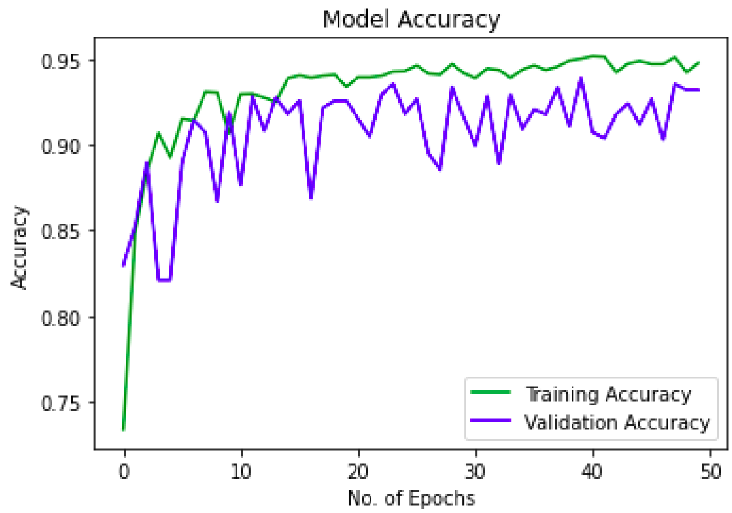

Figure 6: Accuracy plot

7.3 AUC-ROC Curve

- AUC - ROC curve is a performance measurement for the classification problems at various threshold settings.
- ROC is a probability curve and AUC represents the degree or measure of separability. It tells how much the model is capable of distinguishing between classes.
- Higher the AUC, the better the model is at predicting 0s as 0s and 1s as 1s.

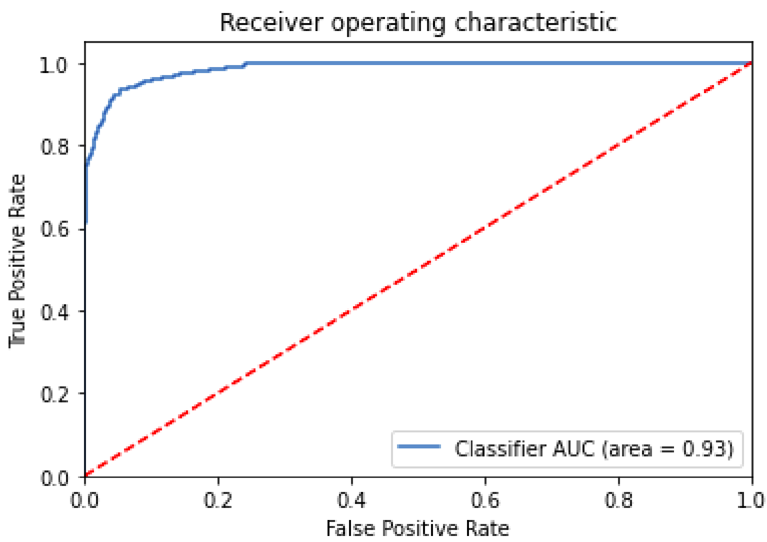

Figure 7: AUCROC Curve