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Cricket Bowling Delivery Detection with Superior CNN Architectures

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Abstract: Delivery in cricket is the sole action of bowling a cricket ball towards the batsman. The outcome of the ball is immensely pivoted on the grip of the bowler. An instance when whether the ball is going to take a sharp turn or keeps straight through with the arm depends entirely upon the grip. And to the batsmen, the grip of the cricket bowl is one of the biggest enigmas. Without acknowledging the grip of the bowl and having any clue of the behavior of the ball, the mis-hit of a ball is the most likely outcome due to the variety in bowling present in modern-day cricket. The paper proposed a novel strategy to identify the type of delivery from the finger grip of a bowler while the bowler makes a delivery. In this project we are training different deep learning algorithms such as CNN, Alexnet, Resnet101, VGG16 and DenseNet to predict cricket ball Grip Type such as 'Arm, Swing, Carom, Flipper, Leg Break and Googly. In this project we created 6 grips dataset by downloading images from Google. We have downloaded images for 6 different grips and dataset contains more than 1000 images. we are training all deep learning algorithms and evaluating their performance in terms of accuracy, precision, recall, FSCORE and confusion matrix. We have coded this project using JUPYTER notebook.

Keywords: cricket bowling, Deep learning, Cricket Bowling delivery Prediction, Performance metrics, Jupyter notebook.

I. INTRODUCTION

Cricket bowling delivery detection is a pivotal aspect of modern cricket, playing a crucial role in performance analysis, strategy formulation, and training enhancement. Traditional methods of analyzing bowling deliveries, relying heavily on manual observation and basic video analysis, often fall short in terms of accuracy and real-time feedback. To address these limitations, advanced technologies, particularly Convolutional Neural Networks (CNNs), have been increasingly utilized for their ability to process and analyze high-resolution data efficiently.

This study aims to revolutionize the detection and classification of cricket bowling deliveries by developing a superior CNN architecture. The proposed framework not only focuses on distinguishing between various types of deliveries, such as fast, spin, and swing, but also ensures real-time processing capabilities for immediate feedback during live matches and training sessions. Leveraging extensive datasets and employing sophisticated data augmentation techniques, the model is designed to overcome challenges posed by limited and varied data quality.

By integrating transfer learning strategies and optimizing the CNN architecture for high-resolution medical images, the research seeks to enhance the model's robustness and generalization ability. This approach not only improves classification accuracy but also provides actionable insights to players, coaches, and analysts, ultimately contributing to better performance and strategic decision-making in cricket. The study's findings and the developed tool aim to set a new standard in cricket analytics, demonstrating the significant potential of AI-driven solutions in sports.

1.1 Cricket Bowling Delivery Detection

Cricket Bowling Delivery Detection refers to the process of identifying and classifying the types of deliveries made by a bowler in cricket. This involves analyzing the bowler's actions and the ball's trajectory, speed, spin, and bounce to determine the specific type of delivery, such as fast, spin, swing, or variations like yorkers and bouncers.

Detection systems use various technologies, including video analysis, sensors, and advanced algorithms like Convolutional Neural Networks (CNNs), to automatically recognize and categorize these deliveries. This information is crucial for players and coaches to assess performance, strategize, and improve training techniques. Cricket Bowling Delivery Detection is the process of identifying and classifying the type of ball delivery executed by a bowler in cricket. This involves a detailed analysis of the bowler's action and the ball's behavior after it is released.

The paper proposed a novel strategy to identify the type of delivery from the finger grip of a bowler while the bowler makes a delivery. The main purpose of this research is to utilize the preliminary CNN architecture and the transfer learning models to perfectly classify the grips of bowlers.

The potentiality of deep learning has reached a new horizon. In recent years, significant increase in research on different fields using Convolution Neural Network (CNN) has been noticed. One remarkable factor of it is that CNN has remarkable accuracy in performing complicated classification by recognizing the complexities in images.

Another most notable factor is the convolution operation that it performs over images using different filters. Invariant characteristics are extracted by the initial convolution layer forwarded to the next layer. Thus its architecture provides the ability to generate the feature vector for further analysis. Not only in academia, but the use of CNN has also gone beyond it. CNN has already shown its potential for huge improvements in the field of medical imaging. For instance, its application in processing reconstructed images in low-cost CT [1] and lung pattern classification from CT scan images [2].

II. LITERATURE SURVEY

2.1 CNN for Classification of Sports There are many successful works with CNN for various sports classification tasks. For instance, [9] proposed a model that is based on Alex Net CNN to classify shots into various types from cricket and soccer videos. Their model showed an accuracy of around 94% which is reported to be better than the accuracy obtained using K-Nearest Neighbors, Support Vector Machine, Extreme Learning Machine and Convolution Neural Network. [10], in contrast, developed a Deep CNN model to classify movements of beach volleyball players based on wearable sensor data. Their model had better accuracy compared to five more classification algorithm they used which suggest that the model is an efficient approach to recognize the sensor-based activity. Likewise, many other works related to sports player detection [11], ball detection [12], and match highlights detection [13] are also available.

2.2 Grip Angle Effect on the Outcome of Spin Bowling In this paper [8], research was performed where they used a sensor attached cricket ball to study the outcome of grip angle parameter on off-spin bowling performance. Their main purpose was to scrutinize whether a standard grip on the ball is better than narrow and wide grips. According to the information of the smart ball they claimed that standard grip is more productive compared to narrow and wide grip in terms of their bowling performance parameter.

2.3 Identification of cricket batting shot from videos with deep learning.

This paper, [14] used saliency and optical flow to get static and dynamic cues and on Deep CNN for extracting representations. They also have stated that their model gives better detection accuracy when they used a multiple class based SVM. Another paper [15] suggested an analogous approach to analyze videos in order to identify batting shots in cricket using deep CNN where they trained their models using LSTM along with 2D CNN and also 3D. According to the result of their experiment, the 3D model had more accuracy compared to the 2D model on their validation data. Their dataset basically consist of around 800 short video clips D. Umpire pose detection with deep learning The following research [16], introduced a unique dataset, called SNOW, for umpire posture detection in cricket which may eventually help developing automatic cricket match highlights generation. They had classified four cricket events namely Six, Wide, No ball, and Out by capturing the action of the umpire from the frames of cricket videos. To extract features they used Inception V3 and VGG 19 and obtained results using an SVM classifier. In their experiment, VGG 19 showed better accuracy for classification compared to that of Inception V3.

2.4 Cricket outcome classification with deep learning This research [17] has used the CNN and LSTM Networks for the outcome classification of cricket. The test accuracy for their classification was 70%. They also made their dataset from collected video clips

III. PROPOSED METHOD

For analyzing different gripping techniques in various kinds of bowling, the methodology that was proposed based on different kinds of CNN Architectures which are respectively: Preliminary CNN model, Vgg16, Vgg19, ResNet101V2, ResNet152V2, DenseNet, AlexNet, MobileNet, InceptionV3, and NasNet. The workflow in Fig.1 gives a brief idea about the way of progress with this analysis. The working began through gathering frames for preparing the dataset.

Then the images are filtered to remove the frames without grips followed by augmentation of the images using Python. The preliminary CNN architecture was then trained to initially test our hypothesis and after achieving better outcomes then the transfer learning models were trained with the images and finally classifying the grip images into 13 classes.

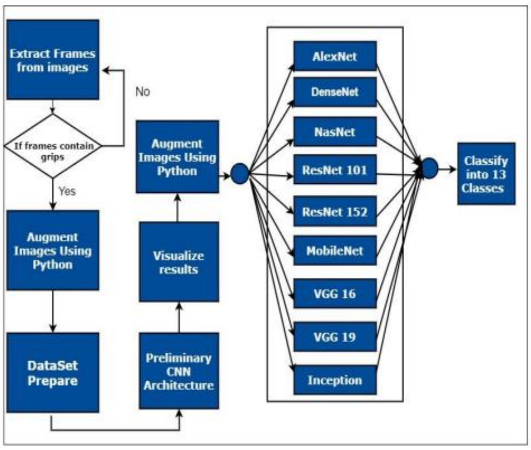


Fig. 3.1 Workflow of Grip Analysis

3.1.1 DataSet

The dataset in Fig.2 that was developed consists of frames extracted from different Real-Time Videos of various bowling experts in offline-mode from YouTube. There are 13 classes of bowling grip images - Inswing, OutSwing, Leg Break, Knuckle, Googly, Doosra, Flipper, Arm, Carrom, Slider, Top Spin, Leg Cutter and Off Cutter respectively. Videos where different bowlers and experts have shown the grips of different bowling techniques were considered. A python script was written using the OpenCV framework to extract the frames from videos automatically.

The images were artificially augmented and used the zoom to focus on the grips of the bowlers. Keras Image Generator were used for this image augmentation, which according to [18], are set-up python generators that convert images to preprocessed tensors to be passed into our models. The main aim was to give best effort to train the models in such a way so that it can accurately classify these images into the type of bowling from grips. Another purpose of image augmentation is to reduce the impact of over-fitting [19] which is a big issue in creating complications and having the worst impact on the training of models. Image generators to zoom 0.2 and make horizontal flips. These images are input to the models where images have reshaped depending upon the models that were used and all images had a channel value of 3 i.e. RGB. Entire data were divided into 77% for training and 33% for testing. Then the models are trained and tested and results have been computed in terms of accuracies and losses.

IV. RESULTS ANALYSIS

In this project we are training different deep learning algorithms such as CNN, Alexnet, Resnet101, VGG16 and DenseNet to predict cricket ball Grip Type such as ‘Arm, Swing, Carom, Flipper, Leg Break and Googly. In paper author has used 5000 images with 13 different grips but this dataset is not available on internet so we created 6 grips dataset by downloading images from Google.

Even I mailed to paper authors to send dataset but they are not replying so I downloaded own images for 6 different grips and dataset contains more than 1000 images. In below screen we are showing dataset details

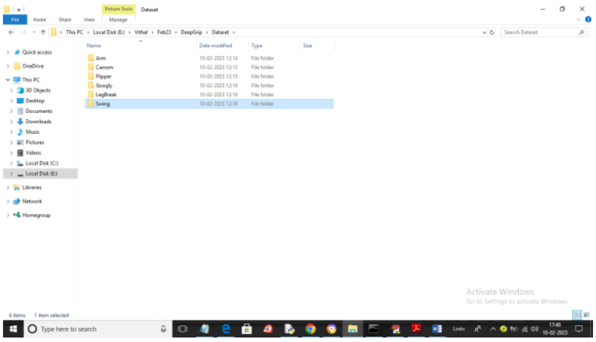


Fig.5.1 Dataset

In above Dataset screen we have 6 different folders and just go inside any folder to view images like below screen

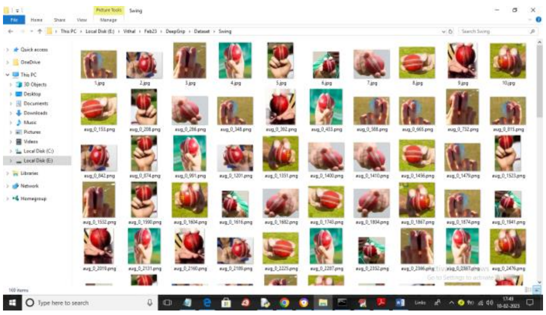


Fig.5.2 training all deep learning algorithms

So by using above images we are training all deep learning algorithms and evaluating their performance in terms of accuracy, precision, recall, FSCORE and confusion matrix.

We have coded this project using JUPYTER notebook and below are the code and output screens with blue colour comments

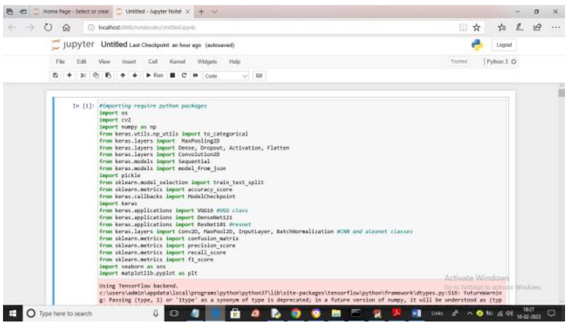


Fig.5.3 are importing all require python classes

In above screen we are importing all require python classes and packages and you can read blue colour comments to know about classes

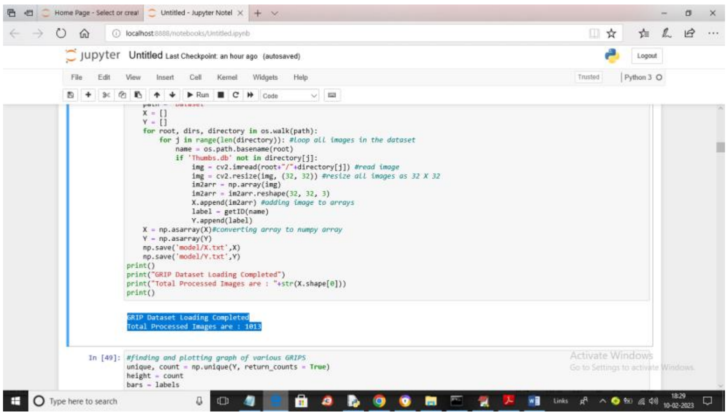


Fig.5.4 connecting to dataset

In above screen connecting to dataset and then looping all images and resizing to equal size as 32 X 32 with 3 channels such as RGB and then adding X and Y array and then in blue colour text we can see total images loaded

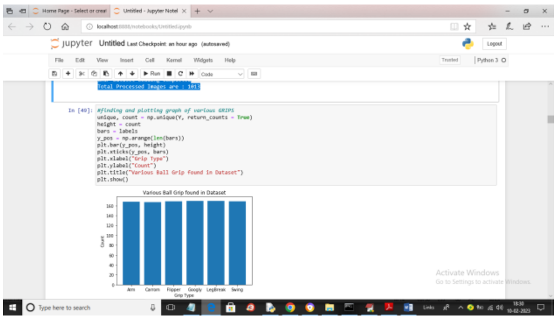


Fig.5.5 Various ball grip found in dataset

In above screen we are plotting graph of different grips found in dataset where x-axis represents grip name and y-axis represents count

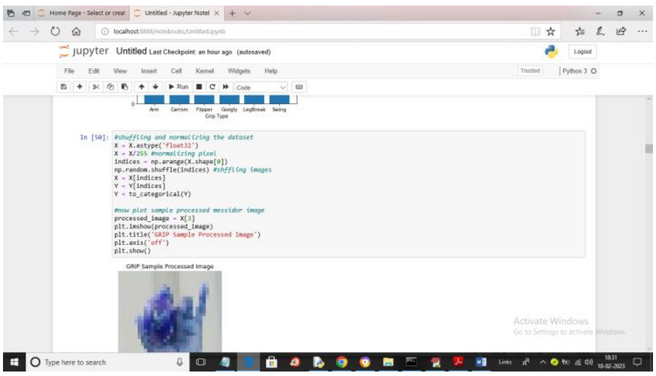


Fig.5.6 processing dataset

In above screen we are processing dataset such as shuffling images and then normalizing pixel values and then displaying one processed image

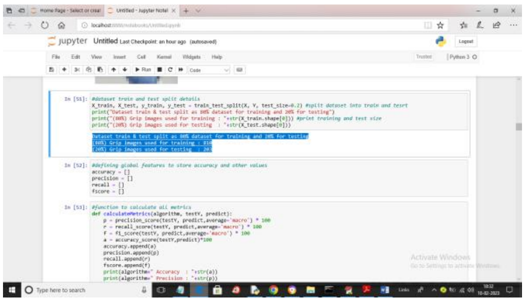


Fig.5.7 splitting dataset into train and test

In above screen we are splitting dataset into train and test where application using 80% images for training and 20% for testing and in blue colour you can see size of images used for training and testing and then defining global variables to store accuracy and other metrics

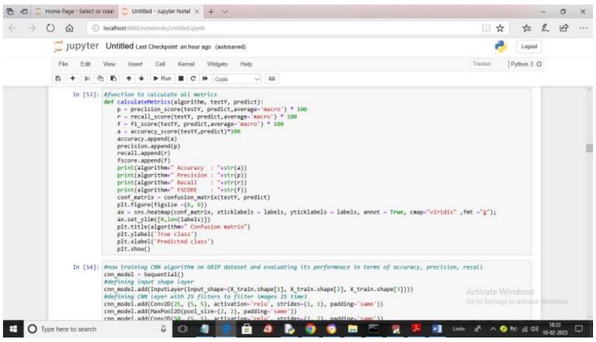


Fig.5.8 defining function to calculate accuracy, precision, recall

In above screen we are defining function to calculate accuracy, precision, recall and other metrics

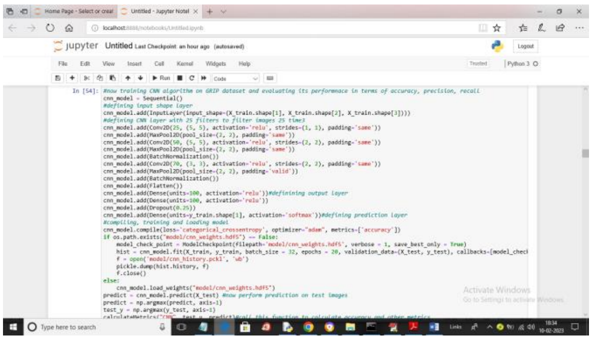
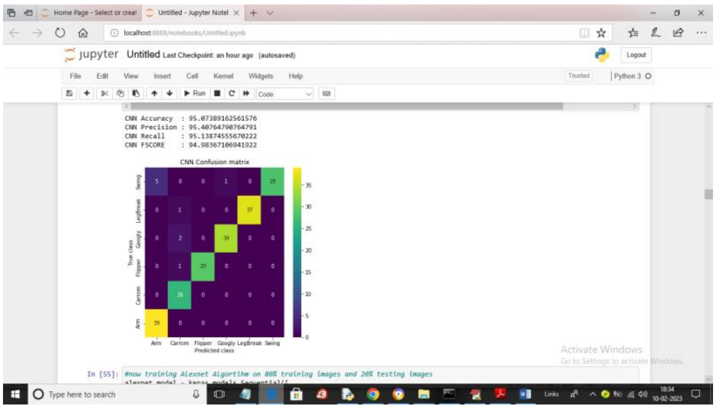


Fig.5.9 defining and training CNN model

In above screen we are defining and training CNN model and after executing above block will get below output



Fg.5.10 CNN confusion matrix

In above screen with CNN we got 95% accuracy and we can see other metrics like precision, recall and FSCORE which we are getting more than 95%. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all blue colour boxes contains incorrect prediction count which are very few. Different colour boxes in diagnol contains correct prediction count which are huge. So CNN in accurate in prediction up to 95%

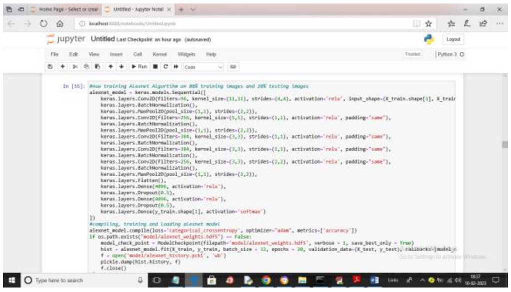


Fig.5.11 code for ALEXNET model

In above screen showing code for ALEXNET model and after executing this algorithm will get below output

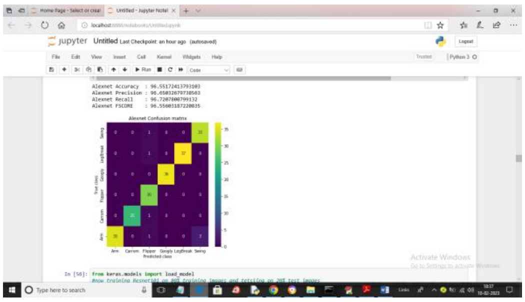


Fig.5.12 Confusion matrix for ALEXNET

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In above screen with ALEXNET we got 96% accuracy and we can see other metrics also

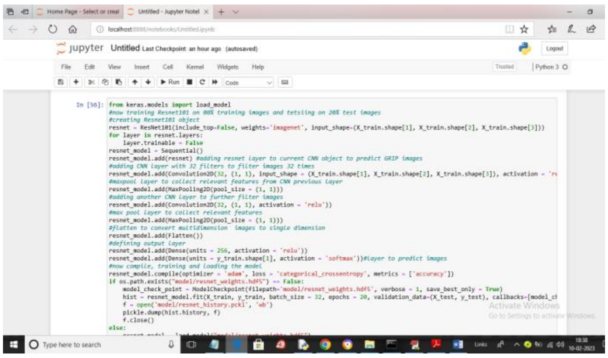

Fig.5.13 training Resnet101 model

In above screen we are training Resnet101 model and after executing above model will get below output

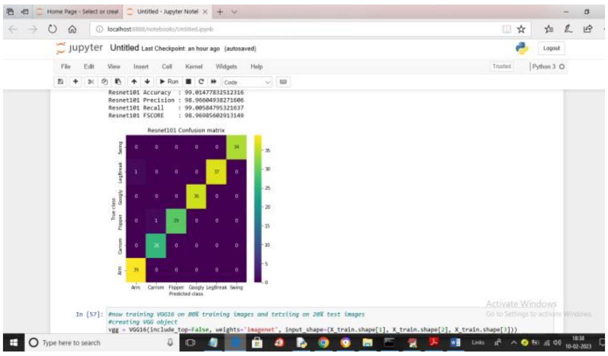

Fig.5.14 Resnet101 we got 99% accuracy

In above screen with Resnet101 we got 99% accuracy

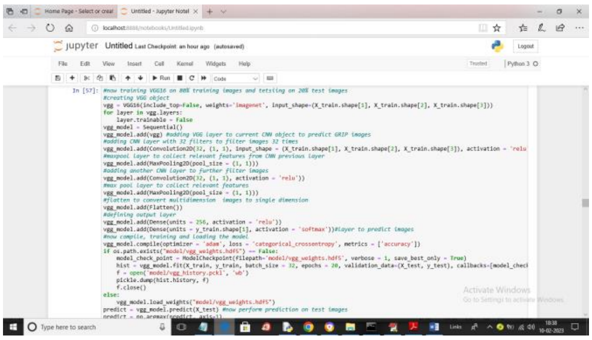

Fig.5.14 training VGG16 algorithms

In above screen we are training VGG16 algorithms and after executing above block will get below output

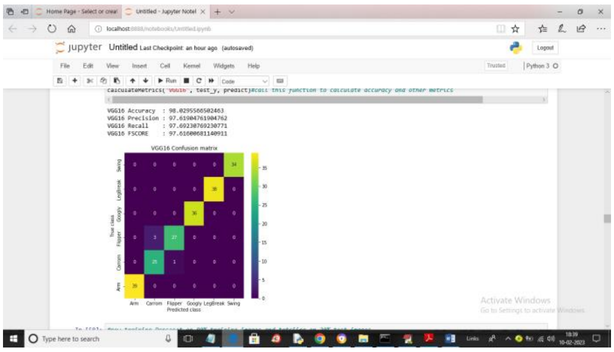

Fig.5.15 confusion matrix for VGG16

In above screen with VGG16 we got 98% accuracy

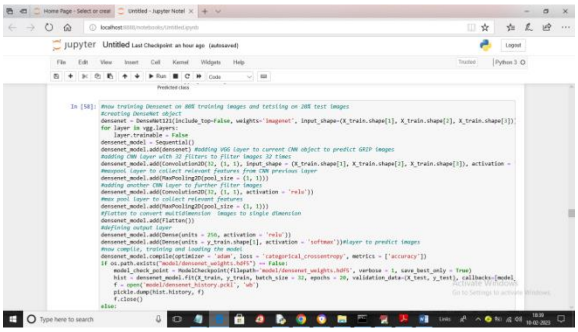

Fig.5.16 training DenseNet121 algorithm

In above screen we are training DenseNet121 algorithm and after executing this algorithm will get below output

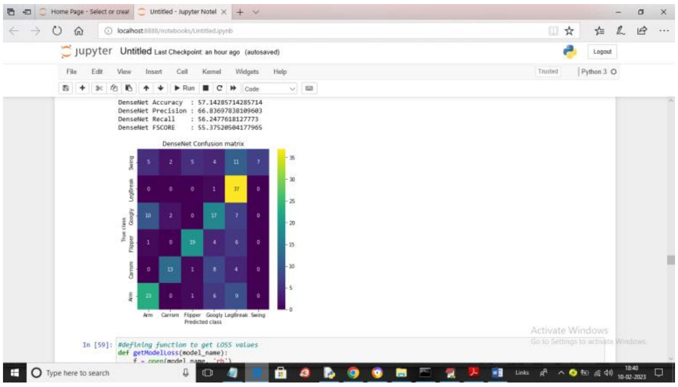

Fig.5.17 DenseNet confusion matrix

In above screen with DenseNet we got 57% accuracy

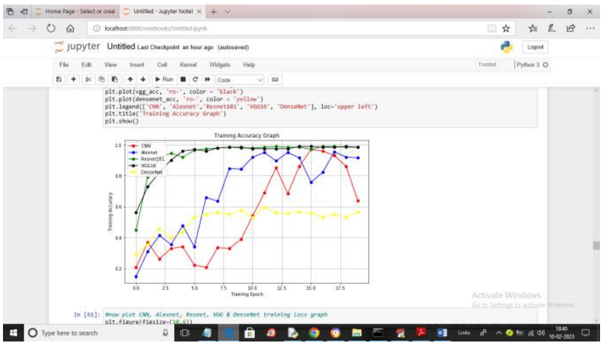

Fig.5.18 Training accuracy graph

In above graph we are showing training accuracy for each algorithm and each different colour line represents accuracy of different algorithm where x-axis represents training epoch and y-axis represents accuracy and with each increasing epoch accuracy get increased

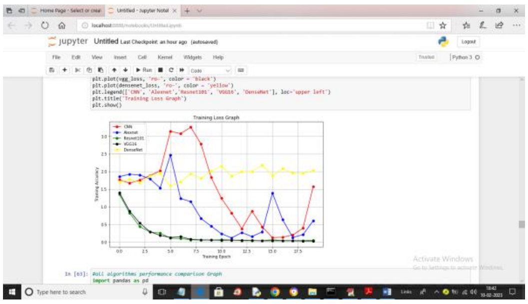

Fig.5.19 loss graph with each increasing epoch

In above loss graph with each increasing epoch loss got decreased

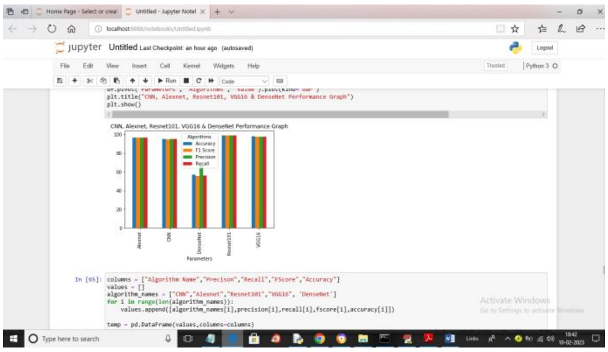

Fig.5.20 Comparison graph for all algorithm

In above graph x-axis represents algorithm names and y-axis represents different metrics such as accuracy, precision, recall and FSCORE in different colour bars and in above graph we can see 4 algorithms has achieved accuracy of more than 95%

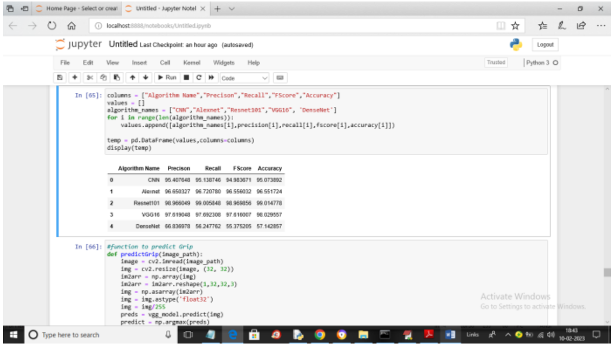

Fig.5.21 algorithm performance in tabular format

In above screen we can see each algorithm performance in tabular format

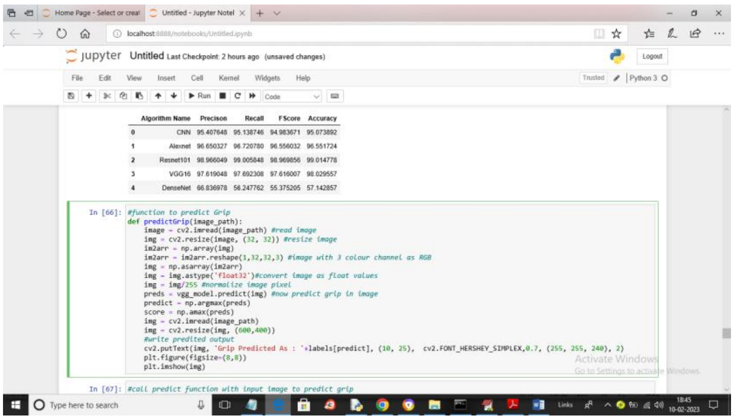

Fig.5.22 reading input image

In above code we are reading input image and then predict type of grip like below output

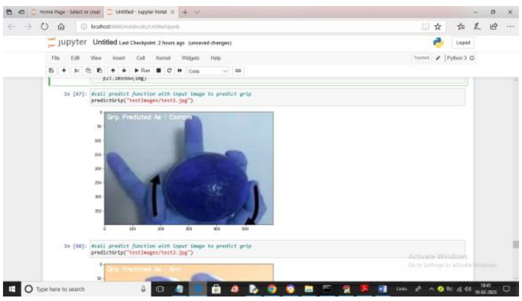

Fig.5.23 grip predicted as 'Carrom'

In above screen grip predicted as 'Carrom' which you can see in white colour text

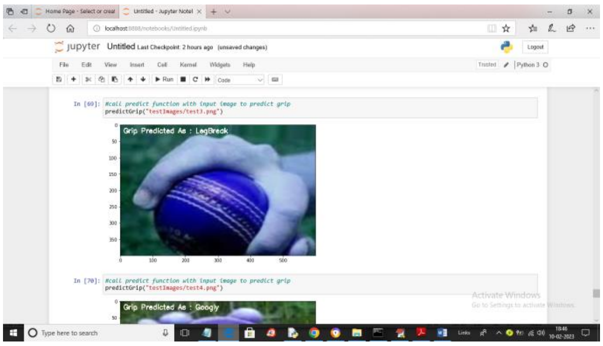

Fig.5.24 grip predicted as Leg Break

In above screen grip predicted as Leg Break

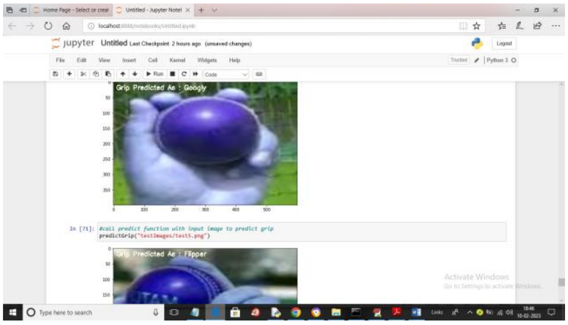

Fig.5.25 other predicted grip output

V. CONCLUSION

In this research a unique strategy was proposed to identify different types of delivery in cricket from offline real-time videos of cricket bowling. A new deep CNN model which was used as a preliminary model to train the dataset showed outstanding accuracy and also compared the model performance with several existing pre-trained transfer learning models. Furthermore, a completely new dataset that consists of over 5000 images, categorized into 13 different deliveries in cricket bowling, was also introduced in the process of this research. This research is likely to be very useful for cricket players and coaches for training with video analysis and also for TV broadcaster of live cricket match to introduce a new technology in their live broadcast. Finally, this research is also expected to serve as a motivation for researchers to apply deep learning to explore various actions and activities related to sports. Moreover, the future scope of this research is wide that may include wrong action detection in a live match, automatic commentary text generation related to bowling action and automatic player performance evaluation.

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