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Deep Grip: Cricket Bowling Delivery Detection with Superior CNN Architectures

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Abstract— *Delivery in cricket is the sole action ofbowling a cricket ball towards the batsman. The outcome of the ball is immensely pivoted on the grip of the bowler. An instance when whether theball is going to take a sharp turn or keeps straightthrough 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 anyclue of the behavior of the ball, the mis-hit ofa ballis 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 thebowler makes a delivery.*

Keywords— *Deep Teaching Convolutional Neural Network AlexNet MobileNet NasNet Grip Dataset Preliminary CNN*

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I. INTRODUCTION

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. Notonly in academia, but the use of CNN has also gonebeyond it. CNN has already shown its potential forhuge 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 REVIEW

[1] H. Chen, Y. Zhang, M. K. Kalra, F. Lin, Y. Chen, P. Liao, J. Zhou and G. Wang, "Low-dose CT with a residual encoder-decoder convolutional neural network," IEEE Transactions on Medical Imaging, pp. 2524- 2535, 2017.

Given the potential risk of X-ray radiation to the patient, low-dose CT has attracted a considerable interest in the medical imaging field. Currently, the main stream low-dose CT methods include vendor-specific sinogram domain filtration and iterative reconstruction algorithms, but they need to access raw data, whose formats are not transparent to most users. Due to the difficulty of modeling the statistical characteristics in the image domain, the existing methods for directly processing reconstructed images cannot eliminate image noise very well while keeping structuraldetails.

Inspired by the idea of deep learning, here we combine the auto encoder, DE convolution network, and shortcut connections into the residual encoder-decoder convolutional neural network (RED-CNN) for low-dose CT imaging. After patch-based training, the proposed RED-CNN achieves a competitive performance relative to the- state-of-art methods in both simulated and clinical cases. Especially, our method has been favorably evaluated in terms of noise suppression, structural preservation, and lesion detection.

[2] M. Anthimopoulos, S. Christodoulidis, L.Ebner, A. Christe and S. Mougiakakou, "Lung pattern classification for interstitial lungdiseases using a deep convolutional neural network," IEEE transactions on medicalimaging, vol. 35, no. 5, pp. 1207-1216, 2016.

Automated tissue characterization is one ofthe most crucial components of a computer aided diagnosis (CAD) system for interstitial lung diseases (ILDs). Although much research has beenconducted in this field, the problem remains challenging. Deep learning techniques have recently achieved impressive results in a variety of computer vision problems, raising expectations that they might be applied in other domains, such as medical image analysis. In this paper, we propose and evaluate a convolutional neural network (CNN), designed for the classification of ILD patterns.

The proposed network consists of 5 convolutional layers with 2 × 2 kernels and LeakyReLU activations, followed by averagepooling with size equal to the size of the final feature maps and three dense layers. The last denselayer has 7 outputs, equivalent to the classes considered: healthy, ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing and a combination of GGO/reticulation. To train and evaluate the CNN, we used a dataset of 14696 image patches, derivedby 120 CT scans from different scanners and hospitals. To the best of our knowledge, this is the first deep CNN designed for the specific problem.

III. METHODOLOGY

Design

For analysing 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 gatheringframes 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 wasthen trained to initially test our hypothesis and afterachieving better outcomes then the transfer learning models were trained with the images and finally classifying the grip images into 13 classes.

IV. Working

A. Data Set

The dataset in Fig.2 that was developed consists of frames extracted from different Real-Time Videos of various bowling experts in offline-mode fromYouTube. 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.

Fig.2. Images from GRIP DATASETB.Preliminary CNN Architecture

The Fig.3 shows a sequential model possesses two convolution layers at the beginning of 250 and 250 kernels respectively with dimensions of [3 X 3] and single stride. The Max Pooling layer of dimensions [3 X 3] then follows these convolution layers to manipulate the size of the input to be passedforward.

Then following four layers are convolution layers with 150, 150, 100 and 100 kernels respectively of the same dimensions as in first 2 layers and then again Max Pooling of [3 X 3] followed the convolution layers.
Finally, the output is flatted and then input into the Fully Connected Network of 100 neurons in the two hidden layers each and then finally through the Softmax Output Layer of 13 neurons according to thegrip classes. The optimizer used is Adam optimizer which according to [20] is an optimization algorithm that has an adaptive learning rate.

C. VGG16 and VGG19

VGG16 is convolutional neural networks of which the architecture is highly successful in the analysis of visual data like images. The images are convertedto [224 X 224] and are input in the VGG16 model.
The Max Pooling Layers in third, sixth, tenth, fourteenth and eighteenth possess a dimension of 2X2and stride of 2. Then the output is flattened andinserted into 4096 units of hidden layers that are connected followed by a layer in the output which consist of softmax activation function. VGG19 isused because of its usefulness due to its simplicity of19 layered architecture.

D. NasNet

NasNet is a CNN architecture which is composedof cells that are enhanced by reinforcement learning [21]. The ImageNet database is used to train NasNet-Large with more than one million images and it can classify 1000 categories of objects.
For our research purpose, the NasNet from KerasApplications were used with pre-trained weights. Theinput size of the images in the NasNet-Large model is[331 X 331].

E. AlexNet and Inception V3

The structure of the AlexNet architecture [4] is such that that it consist of eight layers where the firstfive layers are convolution layers and the remaining three are dense layers that are fully connected. In ourmodel, the same architecture [4] was followed that was proposed by Alex Krizhevsky with the first Convolution layer has size of [11 X 11] with 96 kernels and 4 strides for filtering the input image of [224 X 224 X 3].
After Max Pooling 2D of pool size = [2 X 2], it is again fed into a second Convolution that uses 256kernels with a size of [5 X 5] for filtering. There areagain layers of Convolution where 3rd and 4th layerconvolution has a size of [3 X 3] with 384 kernels and the 5th layer also has a size of [3 X 3] with 256 kernels.

F. DenseNet

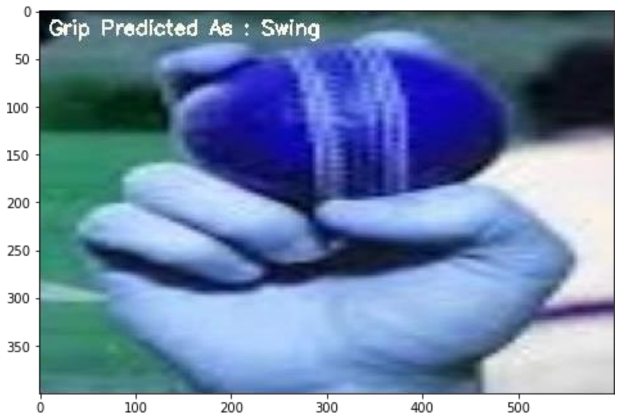
CNN architecture is growing bigger and complicated. According to [23], with increasing layers in CNN, the problem that becomes is that the information in forwarding propagation and the gradient in backward propagation turns out to acomplex value.
However, the DenseNet tries to keep the connectivity between the layers simple and connects each layer directly with each other [23]
[24] [30]. Parameters of DenseNet is much lower compared to traditional CNN models. The networkcontains l layers performing a transformation H□(.)**G.ResNet101, ResNet152 and MobileNet**
ResNet is similar to other networks in terms of its convolution operation. The uniqueness is the identity connection between the layers which makesit a residual network [26]. In 2015, ResNet 152 wasdescribed by its authors [26], as one of the deepest architectures possessing a depth of 152 layers.
The main advantage of using it is that it is one ofthe faster learning models, overcoming the vanishing gradient problem and lower parameters due to increased profundity of the network [27]. Its residual network ensures gradients can move backward directly without going through the activation function and thus less chance of information loss i.e.overcoming vanishing gradient problems.

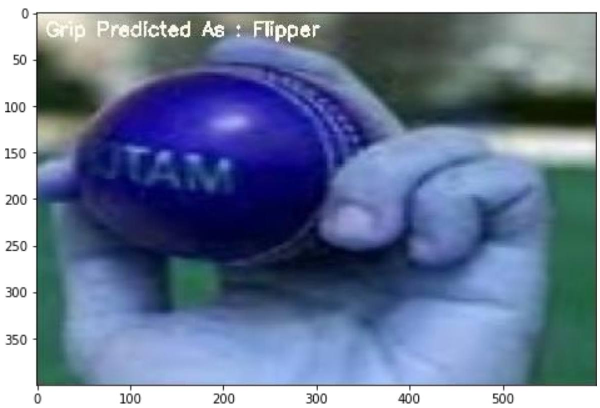
V. CONCLUSION

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 preliminarymodel to train the dataset showed outstanding accuracy and also compared the model performance with several existing pre-trainedtransfer learning models. Furthermore, acompletely new dataset that consists of over 5000 images, categorized into 13 different deliveries in cricket bowling, was also introduced in the processof 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 oflive cricket match to introduce a new technology in

their live broadcast. Finally, this research is alsoexpected 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 wrongaction detection in a live match, automatic commentary text generation related to bowling actionand automatic player performance evaluation.

VI. Expected output





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