Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 5, No.4, May : 2024

DEEP GRIP : IDENTIFYING CRICKET BOWLING DELIVERIES USING CNN ARCHITECTURE

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ABSTRACT

Cricket bowling hinges significantly on the bowler's grip, which plays a crucial role in determining the trajectory and behavior of the ball. As batsmen rely on reading the bowler's grip to anticipate movement and adjust their shots accordingly, accurate interpretation becomes paramount to avoid mistimed shots. In this context, a novel approach is introduced to predict delivery types based on analyzing bowler grips. By leveraging initial CNN architectures and transfer learning models, this method demonstrates promising results in accurately classifying various bowling techniques.The cornerstone of this research lies in the creation of the GRIP DATASET, a comprehensive collection comprising 5573 images extracted from non-live videos. This dataset encompasses a diverse range of 13 ball-holding techniques commonly employed by cricket bowlers. Utilizing this extensive dataset, models such as Vgg16, ResNet101, and DenseNet are trained, achieving remarkable levels of accuracy. Notably, the initial model attains an impressive validation accuracy of 98.75%, highlighting the efficacy of the proposed approach.Moreover, this research represents a significant advancement in the realm of deep learning applied to cricket, particularly in the categorization of finger grip variations. By harnessing technology and computational methods, researchers delve deeper into various facets of cricket, curating datasets aimed at educating computer systems about the complexities of the sport. The utilization of modified VGG16 architecture further enhances the learning process, paving the way for more precise and nuanced analysis.

Efforts are underway to further enhance the accuracy of these models, with a focus on comprehensive cricket analysis. Through continued research and development, these endeavors hold the promise of unlocking valuable insights into the intricate dynamics of cricket bowling. Ultimately, the application of advanced computational techniques offers a pathway to uncovering new dimensions in cricket analysis, with potential implications for player performance optimization and strategic decision-making.

Keywords - Deep Learning,Densenet, Bowling, Finger Grip , Trajectory, VGG16 model, CNN Architecture

INTRODUCTION

The Convolutional Neural Network (CNN), pioneered by Yann LeCun et al. with LeNet-5, revolutionized picture classification and handwriting recognition [1]. CNNs, a cornerstone of deep learning, offer unparalleled accuracy in image classification by extracting invariant features through convolution operations [1]. Widely adopted in medical imaging and by tech giants like Google and Microsoft, CNNs have found increasing use in cricket analysis due to the sport's rich visual and statistical data [1]. Research focuses on grip identification to enhance live match broadcasts and player analysis, leveraging various CNN architectures and pre-trained models [1]. Methodologies encompass literature review, Grip Dataset creation, model development, and outcome visualization [1]. Deep learning techniques extend beyond grip detection to player performance analysis, match prediction,

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and injury prevention, fostering collaborations for innovation in cricket analytics and player optimization [1]. With the potential to revolutionize cricket's strategic approach, deep learning integration continues to evolve, exemplified by AlexNet's performance in the 2012 ImageNet competition [1].

LITERATURE SURVEY

Sports Classification with CNN:

An AlexNet-based CNN achieved 94% accuracy in classifying cricket shots from videos, outperforming K-Nearest Neighbors, Support Vector Machine, and Extreme Learning Machine [4][5]. Another study employed a Deep CNN to classify beach volleyball player actions using wearable sensor data, demonstrating superior accuracy over five other algorithms.

Spin Bowling Grip Angle Study:

A study comparing standard, narrow, and wide grips in spin bowling concluded that the standard grip resulted in superior performance parameters based on smart ball data [5].

Cricket Batting Shot Identification:

A deep learning model accurately identifies cricket batting shots, especially when combined with a multiple class-based SVM [6].Another study utilizes Deep CNN, LSTM, and both 2D and 3D CNN models for shot identification. Evaluation with 800 short videos favors the 3D model, showing its effectiveness in incorporating temporal information for precise recognition.

III. PROBLEM STATEMENT

EXISTING SYSTEM:

Researchers develop a basic CNN software to assess its ability to recognize various ball-grip patterns in cricket. Advanced systems like Vgg16 and ResNet are then trained using a vast collection of images depicting bowlers' grips. This research aims to improve computer-assisted cricket analysis, currently reliant on manual observation. While existing systems track movements in cricket footage, further enhancements are ongoing to increase their speed and accuracy.

PROPOSED SYSTEM:

We propose a CNN-based approach for classifying cricket bowlers' actions, utilizing transfer learning [5]. Popular models like VGG16 were adapted by replacing their final layer for classification [12]. Our dataset, "Bowlers Net," comprised 8100 images of 18 bowlers from seven nations. To prevent overfitting, we employed data preprocessing, augmentation, dense layers, and dropout regularization during training. Grayscale images were initially used, and various optimizers were tested to minimize cross-entropy. Training lasted 150 epochs with RMSProp, using a learning rate of 0.000002 [12].

ADVANTAGES:

It will be quicker to foresee the bowling action; The results will be more precise; and it will take less time to predict the result.

RESULTS & DISCUSSION

13 classes of bowling grip photos have been included in the dataset: Inswing, OutSwing, Knuckle, Googly, Doosra, Flipper, and other.Videos of numerous bowlers and experts demonstrating different bowling types were selected especially for this purpose. The OpenCV framework was employed to build a Python script that automatically extracted frames from the videos.Each class meticulously curated to represent different bowling styles demonstrated by bowlers,experts.The images were digitally boosted through zooming methods that focused on the bowlers' grips.

Preliminary CNN:

The original CNN model comprises two initial convolution layers with 250 [3x3] kernels and one stride. Following are four max-pooling layers [3x3] with 150, 150, 100, and 100 kernels, mirroring the first stage. Flattened output feeds into a fully connected network with two hidden layers of 100 neurons each. The final output is from the softmax output layer, consisting of 13 neurons corresponding to grip

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classes. CNN designs like VGG16 and VGG19 are renowned for their efficacy in visual interpretation, particularly with 224x224 pixel photographs.

The architecture comprises convolutional layers with varying numbers of filters: 64 in the first two levels, 128 in the 4th and 5th sections, 256 in the seventh to ninth layers, and 512 in the 11th to 13th layers. Filters move with a stride of one pixel per convolutional layer. Max pooling layers follow some convolutional layers, with dimensions of 2x2 pixels and a stride of 2 pixels, aiding in dimensionality reduction while preserving key features. Typically, these layers are situated after the third, sixth, tenth, fourteenth, and eighteenth layers of the network.

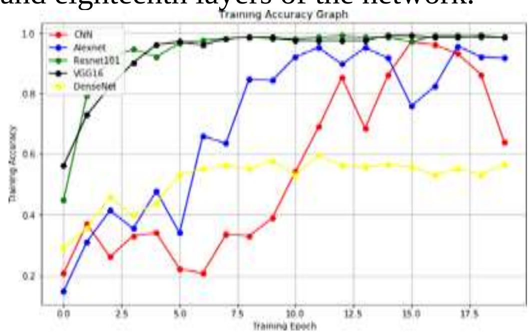

Fig.1 Training Accuracy

NasNet, a CNN architecture, incorporates cells refined through reinforcement learning, enhancing its performance in image classification tasks. Utilizing NasNet provided by Keras Applications, specifically the NasNet-Large model with pre-trained weights, images with dimensions of 331x331 pixels are processed. Trained on the ImageNet database containing over 1 million images classified into 1000 categories, NasNet-Large demonstrates advanced capabilities in image recognition.

RESULTS FOR PROPOSED SYSTEM

This plot tracks the learning progress of different CNNs for a specific task. The x-axis represents training epochs, while the y-axis shows training accuracy. All CNNs, including AlexNet, ResNet-101, VGG16, and DenseNet, improved with more epochs, demonstrating effective learning. DenseNet stood out as the best performer, followed by ResNet-101. However, all models eventually reached an accuracy plateau, indicating limited further learning potential from the training data.

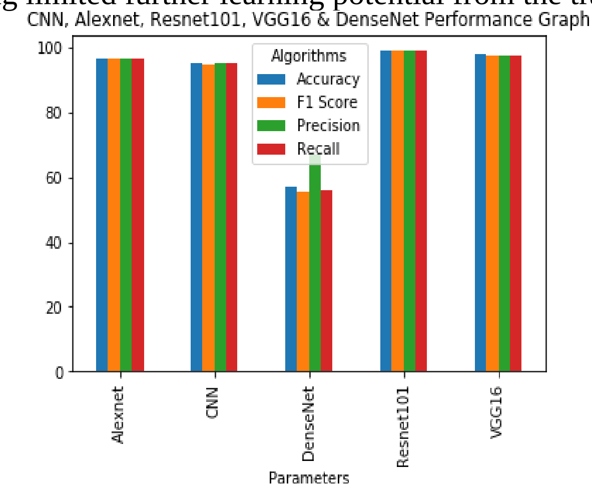

Fig.2 Performance Metrics

The x-axis lists algorithm names, while the y-axis represents metrics like accuracy, precision, recall, and FSCORE as colored bars. Four algorithms attained accuracy above 95%.

CONCLUSION

In this study, we introduced a novel approach to distinguish between cricket deliveries using offline

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videos of bowling. The initial deep CNN model achieved remarkable accuracy. We also compared its performance with various pre-trained transfer learning algorithms. Additionally, we compiled a large dataset containing over 5000 images of cricket bowling deliveries categorized into 13 classes. These findings provide valuable insights for cricket players, coaches, and broadcasters, facilitating preparation through video analysis and enhancing live match broadcasts.

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