# A DATASET AND PRELIMINARY RESULTS FOR UMPIRE POSE DETECTION USING SVM CLASSIFICATION OF DEEP FEATURES

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## **OVERVIEW**

Introduction

**Related Work** 

**SNOW Dataset** 

Methodology

**Results** 





## INTRODUCTION

#### **Present Work**

Sports Video Summarization – Highlights

#### **Approach**

Identify key events from sports videos and use them to automatically generate highlights

#### Cricket

Most popular game in the world after Soccer (2.5 billion viewers)

#### **Key Event Detection**

Role of Umpire

- Authority to make important decisions about events on the field
- Signals these events using hand signals, poses and gestures





#### RELATED WORK

#### **Automatic Highlights Generation**

- Automatic summarization of soccer videos has been proposed
- Similar studies for sports such as basketball, baseball and tennis have also been reported
- Hari et al. Method based on intensity projection profile of umpire gestures for detecting events
- Chambers et al. Fixing wrist bands on umpires for collecting accelerometer data, and using them to classify the gesture of umpires for labelling the events in a cricket video

Benchmark datasets for cricket videos are not available for further development on the existing ideas



## CONTRIBUTIONS AND PROPOSED METHOD

#### **Contributions**

- A Dataset (SNOW) containing images of Umpires for Event Detection
- A System for Automatically Generating Cricket Highlights

#### **Proposed Method**

- Umpire Pose Detection based on Transfer Learning
- Features Extracted on Pre-Trained Networks
- Classification based on Linear Support Vector Machine (SVM)



## **SNOW DATASET**

#### **Umpire**

- 390 Images
- 5 Classes Six, No Ball, Out, Wide (SNOW), No Action
- Each class consists of 78 Images
- Contains Images of Umpires with Different Colour uniforms, camera angles, lighting, etc.

#### **Non Umpire**

- 390 Images
- Contains Images of Team players, Field, Audience, etc.

#### **Source**

Google Images
YouTube Videos

#### **Download Link**

https://goo.gl/zkhVCK





## SNOW DATASET - UMPIRES









Six









No Ball



## **SNOW DATASET - UMPIRES**









Out









Wide



## SNOW DATASET – NO ACTION AND NON UMPIRE IMAGES









No Action







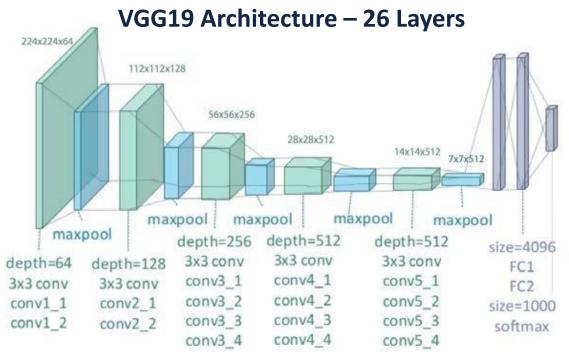


**Non Umpire Class** 

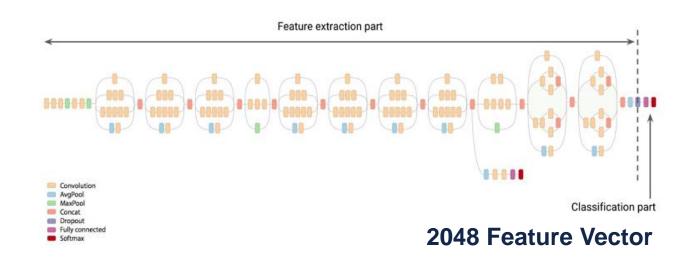


## METHODOLOGY – FEATURE EXTRACTION

Pre-Trained Models on ImageNet Large-Scale Visual Recognition Challenge (ILSVRC)



#### **Inception V3 Architecture – 159 Layers**



**4096 Feature Vector** 

ources:

https://www.researchgate.net/profile/Clifford\_Yang/publication/325137356/figure/fig2/AS:670371271413777@1536840374533/llustration-of-the-network-architecture-of-VGG-19-model-conv-means-convolution-FC-means\_W640.jpg https://software.intel.com/sites/default/files/managed/39/22/detecting-diabetic-retinopathy-using-deep-learning-on-intel-architecture-fig01.png



## METHODOLOGY – CLASSIFICATION

#### **Classification Tasks**

Umpire vs Non Umpire Classifier 1





Linear Support Vector Machine (SVM)
Classifier - C=10

# **Event Detection/Umpire Pose Detection Classifier 2**





## METHODOLOGY – VIDEO SUMMARIZATION

#### **Proposed Method**

- Process each frame of the Video Sequentially
- Buffer every 250 frames and perform event detection
   ~10s of video
- Accumulate Frames into Event Sequences
- Based on Majority Vote sequences are combine into a summary

Input Cricket Video Pre-Processing Frame Extraction and Intensity Normalization Feature Extraction (Pre-Trained Inception V3 Network) (VGG19 Network) Classifier 1 (Not Umpire vs Umpire) Not Umpire Umpire Discard Frame Classifier 2 - Event Detection (Six, No Ball, Out, Wide, No Action) No Action Six, No Ball, Out, Wide Accumulate Frame Sequences Discard Frame No Ball Six Out Wide Majority Vote based Summary Generation

Output every 250 frames -



## RESULTS – CLASSIFIER PERFORMANCE

CLASSIFIED	FEATURES -	Accuracies				
CLASSIFIER		10-FOLD	JACK-KNIFE	TEST	_	
1	INCEPTION V3	96.97%	97.76%	94.23%	_	
	VGG19 – Fc1 LAYER	97.75%	97.59%	96.15%		
	VGG19 – Fc2 LAYER	96.47%	96.79%	94.87%	_	
2	INCEPTION V3	77.71%	77.56%	85.90%	_	
	VGG19 – Fc1 LAYER	82.43%	81.09%	83.33%	_	
	VGG19 – Fc2 Layer	78.14%	81.09%	78.21%	_	

- Inception V3 and FC1 Layer of VGG19 features are selected for Video Summarization performance evaluation
- Classifier was evaluated based on 10-fold validation and Leave-One-Out/Jack-Knife



## RESULTS – CLASSIFIER PERFORMANCE









A





CALL CO.



R

Classifier 1 correctly classifying novel images as non umpire (left) and umpire (right).

Classifier 1 misclassifying both novel images as umpire images.

B

Classifier 2 correctly classifying novel images as OUT (left) and Six (right).

Classifier 2 misclassifying both non umpire images as Six (left) and No Ball (right).

## RESULTS – VIDEO SUMMARY

		ACTUAL	FEATURES					
VIDEO	<b>EVENT CATEGORY</b>	Number	INCEPTION V3			VGG19 - FC1		
VIDEO		OF EVENTS	TP	FP	FN	ТР	FP	FN
<b>V1</b>	Sıx	1	1	0	0	1	0	0
	No Ball	3	2	0	1	2	0	1
	Оит	2	2	1	0	2	1	0
	WIDE	2	2	0	0	2	0	0
V2	Оит	5	5	0	0	5	0	0
TOTAL		13	12	1	1	12	1	1
TRUE POSITIVE RATE			0.9230			0.9230		
POSITIVE PREDICTION VALUE			0.9230			0.9230		

Test Videos V1 and V2 generated

- V1 8 Events
- V2 5 Events

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

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



## RESULTS – VIDEO SUMMARY



False Positive – Umpire image containing no action, but falsely classified as a Out.



False Negative – Umpire signalling a No Ball, but the frame is falsely classified as No Action (left) and the subsequent frame correctly classified as a No Ball (right).



## RESULTS – VIDEO SUMMARY

## Video Demo



## CONCLUSIONS AND FUTURE WORK

#### **Current Work**

- A Dataset (SNOW) containing images of Umpires for Event Detection
- A System for Automatically Generating Cricket Highlights Baseline for this Dataset

#### **Future Work**

- Improvements in Classifier Design
- Improvements to Summarization Technique
- Fine Tuning a Deep Neural Network model
- Other feature extraction techniques

Kimia Lab is currently exploring Dense Net based features



## DATASET AND CODE

#### **SNOW Dataset**

https://goo.gl/zkhVCK



## **Code Implementation**

https://goo.gl/UyBjTa





## **THANK YOU**

A Dataset and Preliminary Results for Umpire Pose Detection Using SVM Classification of Deep Features

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