



Automatic Highlights Generation for Cricket Matches

Alina Sarwar

Why cricket?

- Second most loved game across the globe
- Manual generation of highlights is a cumbersome task.
- Longer duration than most other sports (~3-3.5 hours for T20)
- **Dataset:** 12 T20 match videos and corresponding highlights from official broadcaster

Proposed Methodology

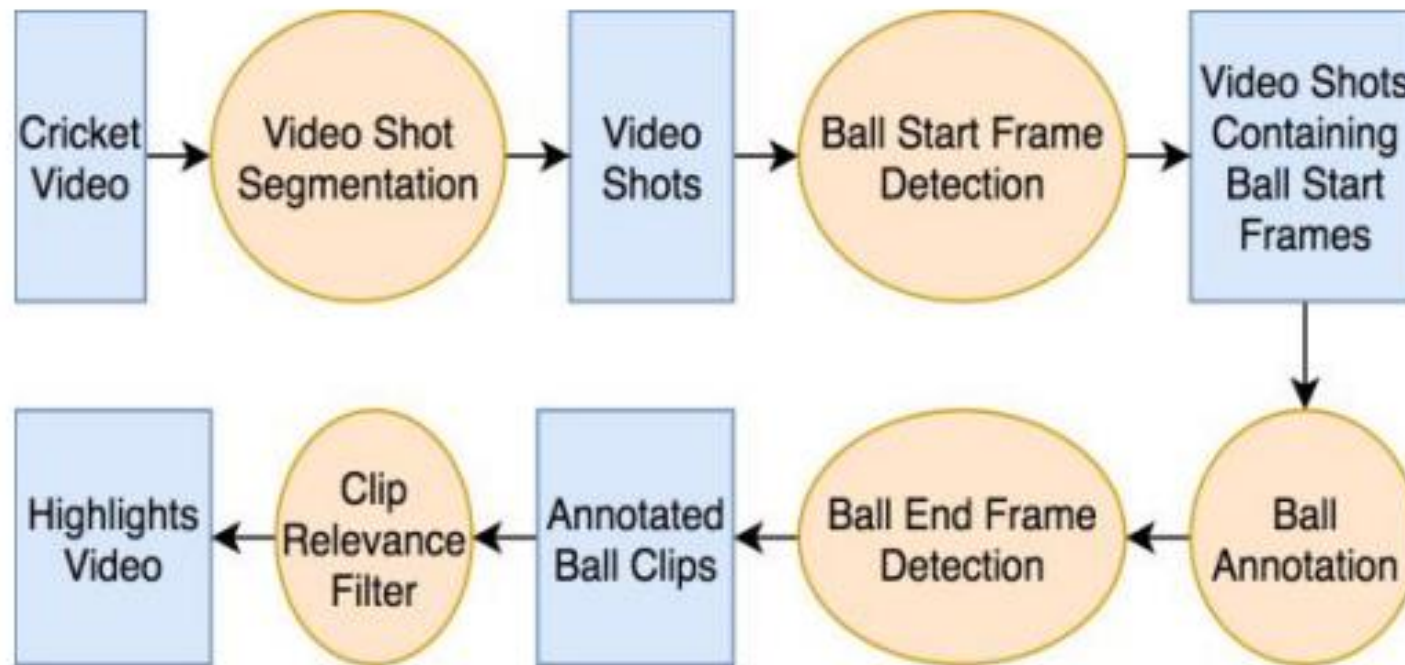
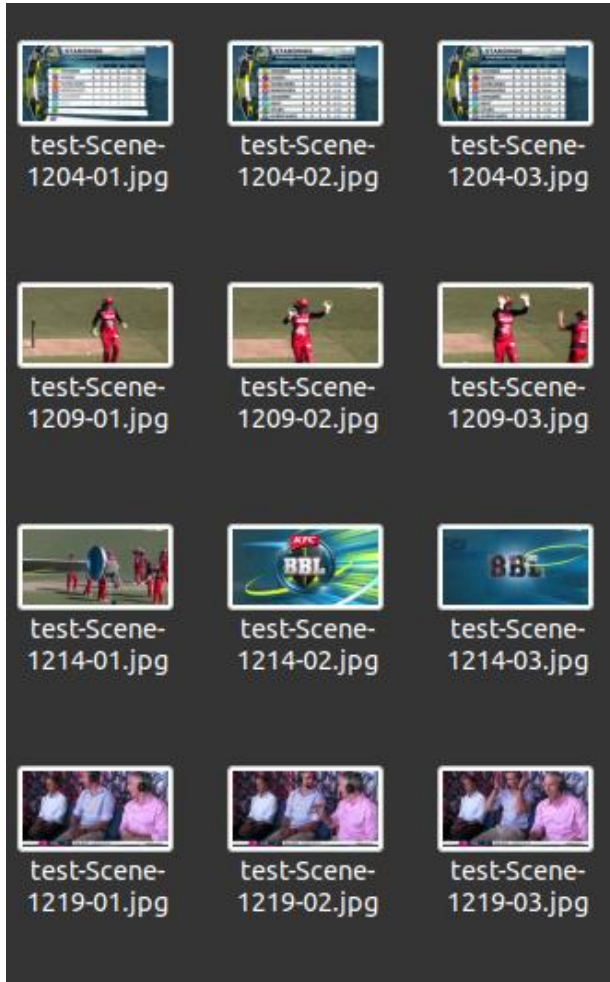


Figure 1: Architecture of proposed approach

Video Shot Segmentation



- Divide complete match video into separate scenes – PySceneDetect
- Dissimilarity between consecutive frames measured using Hue, Saturation, Value
- Each scene is represented by 3 key frames – start, middle, end
- Results saved to csv with start/end timecodes
- Helps cut down processing cost

Figure 2: Sample scenes from a match

Ball Start Frame Detection



Figure 3: Generating potential positive and negative training samples for ball start frame detection

- Train a CNN (binary classifier) for detecting ball start frames
- Prepare potential +/- training samples using image dilations
- If frame difference < threshold, collect as + sample
- Manually review generated samples



Figure 4: Examples of positive samples

~1500 positive samples increased to ~4000 after data augmentation



6 SYDNEY SIXERS
v MELBOURNE RENEGADES
KFC T20 BIG BASH LEAGUE

BIG BASH LEAGUE CAREER		AGE	MTCHS	RUNS
Jason ROY	BATSMAN	27	12	158
Peter NEVILL	KEEPER	32	38	309
Nic MADDINSON	BATSMAN	26	51	1150
Jordan SILK	BATSMAN	26	32	609
Sam BILLINGS	BATSMAN	26	10	200
Johan BOTHA (c)	ALL-ROUNDER	35	50	568
Sean ABBOTT	BOWLER	25	49	272
Ben DWARSHUIS	BOWLER	23	20	122
Daniel SAMS	BOWLER	25	5	0
Will SOMERVILLE	BOWLER	33	7	3
Mickey EDWARDS	BOWLER	23	DEBUT	



Figure 5: Examples of negative samples

~5000 used in training after x10 downsampling

Ball Start CNN Architecture

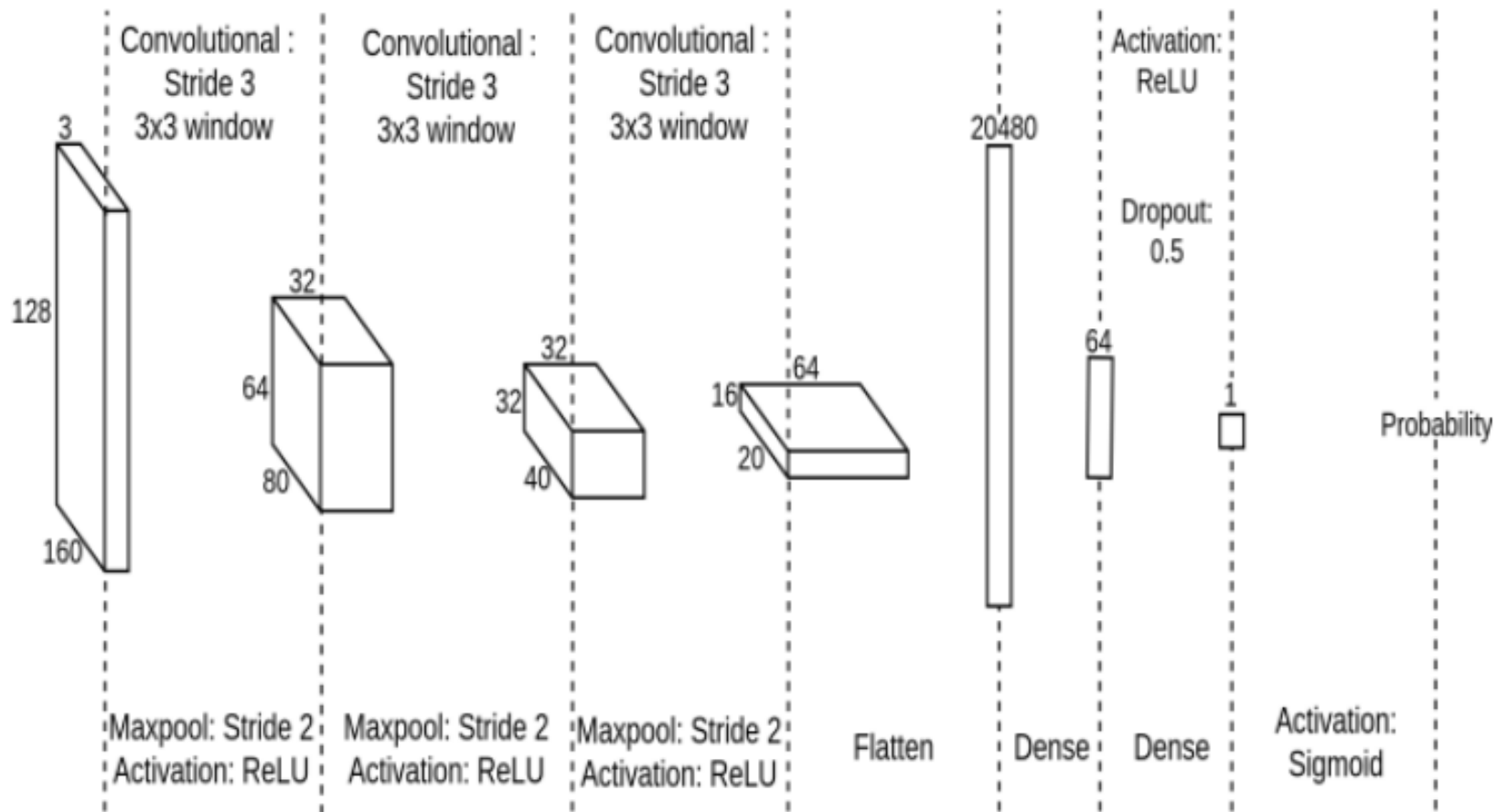


Figure 6: Ball start CNN architecture

Model Training

- RGB frames, downsized to dimensions 160x128
- Train-validation split: 80:20 – with stratified sampling to maintain equal class proportions in each set
- ~450 test images
- Loss Function: Binary Cross Entropy
- Learning Rate: 0.0001

Model Training

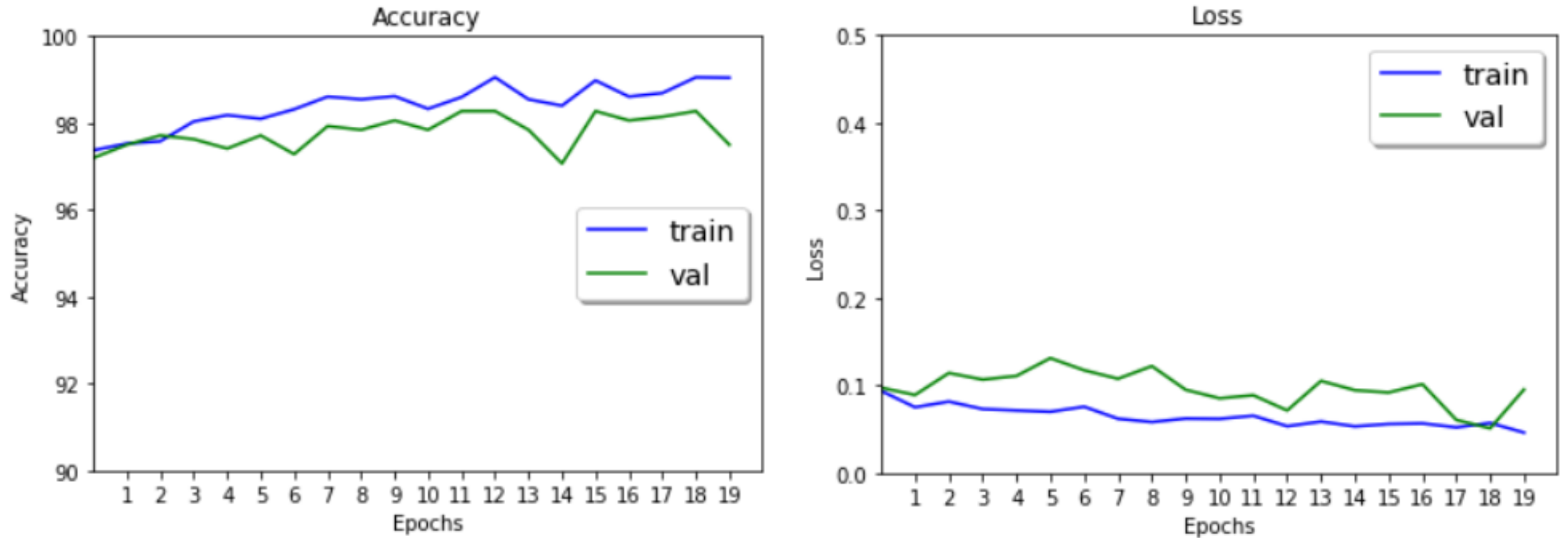


Figure 7: Training statistics

Model Results

- Model weights saved at the best validation accuracy
- Test Accuracy: 98.25%
- 8/458 incorrect predictions - mostly labelling errors



Figure 8: Visualizing wrong predictions

Further steps..

- Find model predictions on the bulk of negative samples originally collected and incorporate any false positives in the training set
- Switch color channels and convert images to gray scale as part of data augmentation
- Rerun an iteration of training

Project milestones

- **Phase I progress update**
 - Dataset acquisition
 - Generation of scene clips
 - Generation of training samples for CNN
- **End of Phase I**
 - Complete training of CNN
- **Phase II progress update**
 - Complete OCR implementation for detecting ball end frame
 - Ball clip annotations
- **End of Phase II:**
 - Final highlights generation
 - Debugging + code clean ups
 - Evaluation of results and reporting

- Player specific highlights
- Customized highlights generation based on personal preferences



Questions?