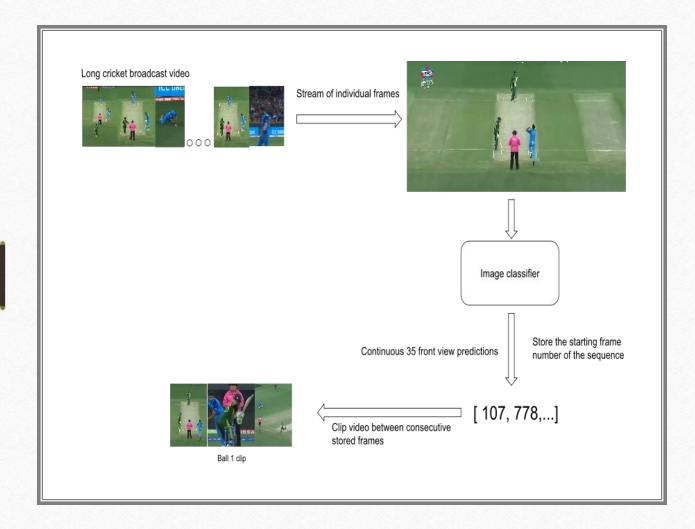


### **Data set Creation**

- Full-length T20I match videos were downloaded from YouTube and manually clipped ball-by-ball to create ~480 video segments.
- Each clip was labelled into four event categories: Run, No Run, Boundary, and Wicket.
- A separate image dataset (~1000 samples) was created for view classification, with balanced classes for **Front View** and **Not Front View**.

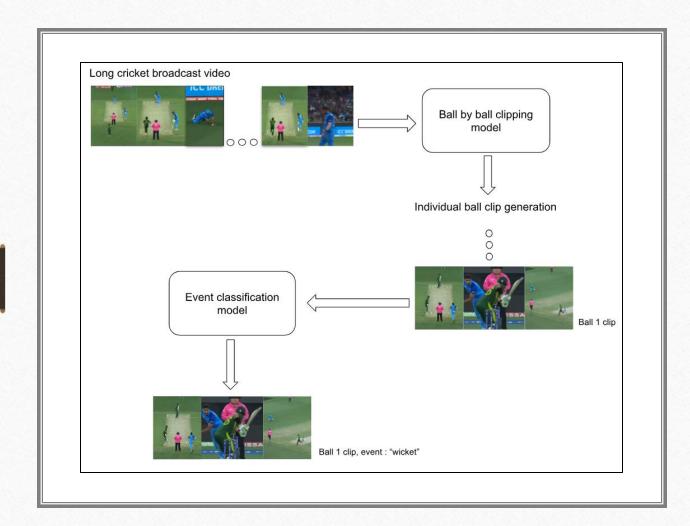
### Challenges Data set Creation

- Class Imbalance: Wickets and Boundaries are rare → applied data augmentation
- Scoreboard Bias: Scoreboard was removed to avoid model overfitting



# Flowchart of the model for clipping individual ball clips from a broadcast video.

- Here the CNN model determining weather a frame is a front view frame or not
- If it is, it marked it as a start of a ball.



## Flowchart of the model for classifying individual ball clips into particular class.

- Here the LRCN model determining weather this clip is a wicket, run, no run or boundary.
- It gets its input from the previous CNN model.

### Conclusion

- Our deep learning approach to cricket event classification and highlight generation demonstrates the potential to transform the cricket viewing experience. By automating event classification, we address some key imitations.
- 1. Expanding the dataset to improve classification accuracy, particularly for rare events like wickets. Also approach to automate the dataset creation process.
- 2. Exploring more advanced architectures, such as 3D CNNs or transformer models, to better capture temporal dynamics
- 3. Integrating additional features such as player tracking and shot type classification

