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An optimization based deep-LSTM predictive analysis for decision making in cricket

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Abstract. This paper focuses on developing a system that provides support to the on field umpire in cricket in order to make decisions like leg before wicket using two cameras placed at on-field umpires position so that the cameras can capture video, where the batsman has been attempted to play the ball. Initially, these videos are processed to obtain the ball movement data by implementing background subtraction and spatial tracking. A new technique named as spider-squirrel optimization-based deep long short-term memory (SSO-based deep LSTM) is proposed to perform the path prediction after the batsman intercepts the ball. Finally, the prediction path result is obtained using the first camera video and the second camera video, which is considered to analyze the leg before wicket event with the help of predictive confidence-based decision. The effectiveness of the proposed SSO-based deep LSTM is computed and revealed a mean square error (MSE) of 1.107.

Keywords: Background subtraction, spatial tracking, deep long short-term memory, spider-squirrel optimization, and mean square error.

1 Introduction

Intelligent video surveillance (IVS) is broadly utilized in accident detection, patient monitoring, traffic control, and public security [1], [2]. Object tracking becomes very popular in computer vision and surveillance-related tasks. The tracker is utilized to search the continuous labels of moving objects over time. Trajectory path detection is utilized in traffic management, automatic visual surveillance, sports video analysis, suspicious activity detection, and so on. The mean shift tracking algorithm (MS) is utilized for selecting the probability distribution of the pixels in the target region as a tracking feature with low complexity and high execution efficiency [3]. In the Bayesian estimation theory, the KF has a good prediction probability of location in the next moment accompanied with a fast convergence speed. The LSTM model [4], [5] associates LSTM with the social pooling layer and predicts trajectory as the sequence generation.

In cricket, the high expense and number of technical requirements of tracking technologies restricted their usage in any matches, training academies, and competitions other than the matches played at an international level. For these applications, computer vision seems to be the best option but there are very few computer vision algorithms and systems that operate at a low cost to enhance the experience of cricket.

One such high cost and infrastructure involved system in cricket analysis is Hawk-Eye [6] where six synchronized cameras are fixed around the ground field, as shown in Figure 1. These cameras track the ball's moment while the bowler releases the ball from hand until the required location on the field. Two sets of three cameras are gen-locked which makes usage of six cameras. The Hawk-Eye system makes images into a 3D image which then calculates where the ball pitched, interception of batsman's pad is done manually and the lateral movement is extended further off /beyond the wickets.

The third umpire with a set of many assisted technical persons will make use of this for making LBW event decisions with computers making processing of the video. Despite being successfully illustrated on TV, it has some problems: visibility, accuracy, and calibration of cameras, cost, robust communication, speed of computation, replacement in the case of a sudden fault, etc.

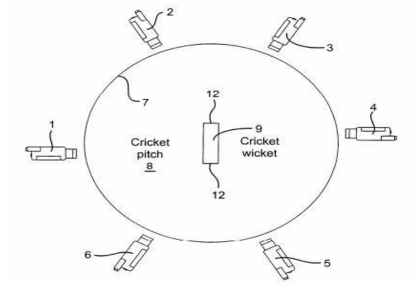


Fig. 1. Hawk-Eye Setup

This research is focused to design the trajectory prediction by proposing an SSO-based deep LSTM classifier using two cameras. The proposed approach involves the following phases, namely frame extraction, moving object detection, ball object identification, spatial tracking of ball object, hitting point identification, and the path prediction for camera-1 and 2.
The major contribution of this research is SSO-based deep LSTM classifier for path prediction. An effective trajectory prediction mechanism is developed using the proposed SSO-based deep LSTM for predicting the trajectory from the input video. The path prediction process is performed on the basis of the deep LSTM classifier [7] in order to predict the path effectively, such that the weights of the classifier are trained using the SSO algorithm.

2 Motivation

In years after the change in cricket format, new methods are included and umpires have more weight to carry apart from making decisions, i.e. carrying a camera fixed on their head cap. The purpose of using this is limited to provide entertainment given to the viewers of a cricket match. The idea of utilizing the information gathered from this facility motivated to carry out the research work to analyze the LBW event which also addresses few drawbacks of hawkeye i.e. cost, time and manpower.

3 Related Work

Sk. Arif Ahmed et al.[8] modeled a Fusion-based approach for detecting the trajectory by selecting the trajectory which is accurate from the given trajectories. The trajectories are generated independently by using two tracking algorithms namely, L1APG and CT, and fused them using an unsupervised classification method to select a better trajectory.

Zhen-tao Hu et al.[9] developed a video target tracking approach using the prediction and re-matching strategy under occlusion conditions. Initially, the Mean Shift algorithm was combined dynamically with the Kalman filter to obtain tracking of the unoccluded target. After that, to estimate the position of the occluded target, the Kalman filter was integrated with target prior information. At last, the process of the occluded targets was re-matched using normalized cross-correlation for obtaining the optimal position of the target accurately and quickly.

Graham Thomas et al. [10] presented an overview of computer vision applications for sports analysis and their challenges. The multi-camera ball tracking application provides detailed information for aiding the referee, coaching, and providing reviews to TV viewers. The applications for tracking players which are used for tactical analysis depends on semiautomated approaches.

Daniel Chalkley et al. [11] conducted a study to examine the ball flight prediction accuracy for determining LBW in cricket by using three cameras video based decision making tasks. Participants have viewed videos that represented the umpire's perspective and asked to estimate the final location of the ball at the stumps under temporary occlusion conditions by using a computer cursor. This study indicates that further research is required on perceptual-cognitive demands and other factors like removal of environmental influences like wind and pitch changing conditions, knowledge, and bowler's past history.

C J Baker [12] presented a method to determine the trajectories of cricket ball in the middle of bowler and batsman using the aerodynamic forces on cricket balls. This method uses the full trajectory equations developed to study the debris flight in severe windstorms. The presented method can calculate trajectories of all bowling speeds of different ball types and can also handle complex trajectories that involve late and reverse swing.

Clare Mac Mahon et al. [13] presented a study to address the factors that impact the decision making of a referee in a basketball game, where basketball officials were shown video clips and asked to detect infractions and fouls to test their ability in detection. In the proposed study, knowledge-priming and infraction-priming were given to the referees. This study explains the complexity in decision-making of the referee in infraction-detection and indicates the necessity to consider key features such as positioning, time pressures, low and high-frequency fouls while creating training and testing tools to affect processing information and decision making.

David C Southgate et al. [14] conducted a descriptive study to determine the accuracy of cricket umpire's ability to take leg-before-wicket decisions and to investigate whether the decision-making accuracy is affected when umpires monitor the feet of bowler's feet while delivering the ball. In the proposed study, four umpires have reported their judgements based on conditions specified in rules i.e., observing the front foot of the bowler, observing back foot of the bowler before delivering the ball, no foot condition. To assess the accuracy of responses given by umpires, video recording aided by the use of superimposed wicket to wicket lines is utilized. The results indicate that the umpire's performance would be improved by relieving the umpires from judging no-ball deliveries.

Qiaokang Liang et al. [15] developed a deep learning approach for basketball detection. Here, the basketball detection model was trained using Region-enabled FCN that considers the ResNet as a network backbone. Also, Soft-NMS, multi-scale training strategy, and OHEM were included for achieving higher detection accuracy. The method was faster and highly effective for basketball detection but failed to detect the basketball that is occupied entirely by the players.

Young Yoon et al.[16] developed an approach for recognizing the basketball players and their interaction with the athletes. Also, the Yolo was used for detecting and classifying the objects. However, the player tracking approach was introduced for performing better under a poor condition in which the camera angle changes and shifts dynamically.

Qiuli Hui [17] presented the Mean Shift algorithm for motion video tracking in the sports. Initially, the prediction method was introduced for locating the target location, and then the iterative calculation was made on the Mean-shift algorithm for determining the true location of target. The method guarantees real-time tracking and reduces the computational complexity and time consumption but the track objects with similar background color were not considered.

Longteng Kong et al. [18] developed a joint framework for action recognition and tracking of athletes. Here, the scaling and occlusion robust tracker, named SORT was introduced for localizing the location of a specific athlete in every frame. Also, the scale refinement was achieved based on Edge Box (EB) and the occlusion recovery was performed using the candidate obstruction. Moreover, LRRCN was established to obtain tracking results.

Shuangfu Guan and Xiaofeng Li [19] presented the Kalman filter for moving target tracking and the trajectory generation in the sports videos. Initially, the location and ten ID information on objects blob were received through image segmentation. Then, the Kalman filter and the centroid tracking algorithm was introduced for improving tracking precision.

Jiaxu Wu et al.[20] presented an approach for the pedestrian trajectory prediction. This framework used the encoder-decoder framework based on BiRNN. The major problem of integrating social interactions was addressed by BiRNN.

4 Proposed Methodology

4.1 System Description

The general system of our multi-camera tracking is illustrated in Figure 2.

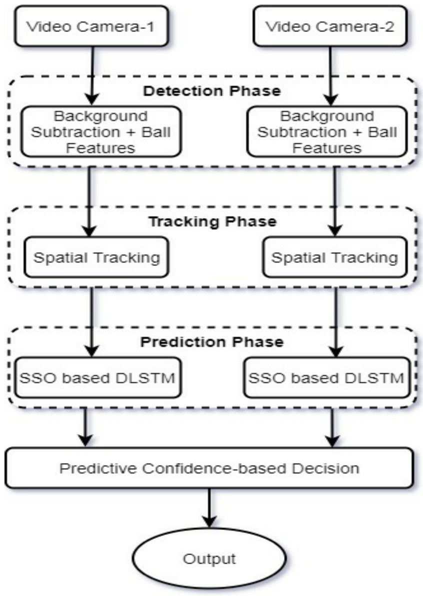


Fig. 2. Overview of the Proposed System

This section elaborates on the proposed method for trajectory prediction using the proposed SSO-based deep LSTM. Two cameras are located as specified in Figure 3(c) which captures the ball moving towards the batsman. Initially, the video capturing the hit-ball by batsman or batsman body is taken from camera-1 (front view) and the selected video is subjected to the frame extraction phase, and then the extracting frames are given to the moving object detection phase.

Here, the moving objects are detected based on the background subtraction. After detecting the moving objects, the ball objects are identified based on shape, size, and color. Once the ball objects are identified, the spatial tracking of ball objects has also performed. Finally, the path prediction is performed using deep LSTM, which is trained by the proposed optimization algorithm called SSO. The proposed algorithm is inspired by two metaheuristic swarm intelligence algorithms namely, SMO [21] and SSA [22], which aims to solve optimization challenges. Thus, the predicted path is obtained from camera-1. On the other hand, the same steps are followed for the video captured by camera-2 (side view) in order to obtain the prediction path.The result of the prediction path is obtained using the first video and second video are fed to the predictive confidence-based decision to deliver the final output.

4.2 Object Detection using Background Subtraction Model and Ball Features

Once the keyframes are extracted from the input video, the extracted keyframe is given to the object detection phase which uses background subtraction (to detect the moving objects). It is also utilized for localizing and obtaining the centroid of connected pixels moving on the foreground. This approach aims to detect the moving objects by calculating the difference between the present frame and the background image or the background model. The output obtained from the moving object detection is a batsman with bat and ball. After the detection of the moving object, the ball object is identified based on size, shape, and, color. This step is very necessary for finding the ball object to predict the path effectively.

4.3 Object Tracking

This section presents the spatial tracking of the ball object. Here, the features of the object are taken to determine the location of the ball in the initial frame where the object appears. Based on the direction of spatial coordinates i.e., (x,y) from the initial frame, the object is tracked in the next frame. Again, the location of the same object is tracked in the consecutive frame, and so on until the required keyframe. Now, these tracked locations are used to identify pitching and impact of the ball using the below algorithm 1.

```
Algorithm 1: Sequential Decisions
Input: Ball Locations
Output: Pitching and impact locations
for 1 to size(ball locations)
        if change in Y
                pitching location
        end if
end for
for pitch _loc to size(ball locations)
        if change in Y
                after_pitching(k)=ball_loc (pitch _loc)
                k=k+1
                count=1
        else
                if count is 0 and change in X
                        after_pitching(m)= ball_loc (pitch _loc)
                        j=j+1
                        m=m+1
                else
                        break
                end if
        end if
        impactlocation=after_pitching(end)
end for
```

The algorithm 1 takes all the ball locations in terms of spatial coordinates (x,y) from the video and finds the first deflection i.e change in Y's value (increasing to decreasing). Now, this deflection is considered pitching as the ball hits the ground and bounces. Now the impact location is found from the remaining ball locations by finding the next deflection of either or both x's and y's coordinates of ball location. This deflection location is considered as impact location. For the ball bowled full toss to the batsmen, the first deflection is considered as an impact location.

4.4 Path Prediction and Analysis

After identifying the impact point based on algorithm 1, the deep LSTM [7] classifier is utilized to predict the path. The conventional deep learning classifiers using sigmoidal activation units suffered from vanishing gradient problem. This may lead to information loss with time because of decaying gradient values through layers. This problem effectively utilized multiplicative input, forget gates, and output gates for preserving the state information. As deep LSTM holds several benefits than the other classifiers, it is highly effective for achieving path prediction using the memory cell of the classifier. Here, the memory cell is utilized to store the state information, and it acts as an accumulator.

Training of deep-LSTM using Spider-Squirrel optimization algorithm. This section elaborates on the learning method used to estimate the weights of deep LSTM using training data. However, the objective function of the path prediction is optimized using the proposed

SSO. The main aim of SSO is to train deep LSTM with the optimal weights. The SMO [21] is very efficient for training and is flexible in swarm intelligence-enabled algorithms and improved computing speed. The disadvantage of SMO is minimal convergence and is highly sensitive to the hyperparameters. On the other hand, SSA [22] is motivated by the dynamic searching behavior of squirrels and it is an effective way for locomotion also known as gliding. The behavior of squirrels is formulated mathematically considering the features of food search. The SSA attains global optimal solutions with enhanced convergence behavior. The effectiveness of SSA is more precise and consistent and provides effective solutions for real-time issues. Here, the drawbacks of SMO are resolved by SSA that provides an optimal convergence rate. Thus, the integration of SSA and SMO enhances the overall system working of the algorithm.

The equation to update the position in SMO is as follows:

$$Y_{hp}^{u+1} = Y_{hp}^{u} + N(0,1) \times \left(F_p - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right) \quad (1)$$

The SSA [22] is employed to address the real-world issues, as they avoid local optima by exploring the search space and global optimum. SSA algorithm is highly efficient and offers a better performance while evaluating the solutions, and only less parameter is required for fine tuning and the SSA algorithm is employed due to its simpler algorithmic structure. As per the SSA algorithm, the solution update is expressed as,

$$Y_{hp}^{u+1} = Y_{hp}^{u} + O_k \times G_l \left(Y_g^{u} - Y_{hp}^{u}\right) \quad (2)$$

$$Y_{hp}^{u+1} = Y_{hp}^{u} + O_k G_l Y_g^{u} - O_k G_l Y_{hp}^{u} \quad (3)$$

$$Y_g^{u} = \frac{Y_{hp}^{u+1} - Y_{hp}^{u} + O_k G_l Y_{hp}^{u}}{O_k G_l} \quad (4)$$

After substituting equation (4) in equation (1), the obtained equation is given as,

$$Y_{hp}^{u+1} = Y_{hp}^{u} + N(0,1) \times \left(\frac{Y_{hp}^{u+1} - Y_{hp}^{u} + O_k G_l Y_{hp}^{u}}{O_k G_l} - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right) \quad (5)$$

$$Y_{hp}^{u+1} = Y_{hp}^{u} + \frac{N(0,1) Y_{hp}^{u+1}}{O_k G_l} + N(0,1) \times \left(\frac{O_k G_l Y_{hp}^{u} - Y_{hp}^{u}}{O_k G_l} - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right) \quad (6)$$

$$Y_{hp}^{u+1} - \frac{N(0,1) Y_{hp}^{u+1}}{O_k G_l} = Y_{hp}^{u} + N(0,1) \times \left(\frac{O_k G_l Y_{hp}^{u} - Y_{hp}^{u}}{O_k G_l} - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right) \quad (7)$$

$$Y_{hp}^{u+1} \left(1 - \frac{N(0,1)}{O_k G_l}\right) = Y_{hp}^{u} + N(0,1) \times \left(\frac{O_k G_l Y_{hp}^{u} - Y_{hp}^{u}}{O_k G_l} - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right) \quad (8)$$

$$Y_{hp}^{u+1} \left(\frac{O_k G_l - N(0,1)}{O_k G_l}\right) = Y_{hp}^{u} + N(0,1) \times \left(\frac{O_k G_l Y_{hp}^{u} - Y_{hp}^{u}}{O_k G_l} - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right) \quad (9)$$

Thus, the final update equation of the proposed SSO algorithm is expressed as,

$$Y_{hp}^{u+1} = \frac{O_k G_l}{O_k G_l - N(0,1)} \left[Y_{hp}^{u} + N(0,1) \times \left(\frac{O_k G_l Y_{hp}^{u} - Y_{hp}^{u}}{O_k G_l} - Y_{hp}^{u}\right) + N(-1,1) \times \left(Y_{tp}^{u} - Y_{hp}^{u}\right)\right] \quad (10)$$

Where,

Y_g^u: best location

Y_{hp}^u: current location

Y_{tp}^{u}: random location

F_p: mean of ball locations

Y_{hp}^{u+1}: next location

O_k: random gliding distance

G_l: Gliding constant and

N: random number

By integrating the optimal features of SSA with SMO, the performance of path prediction can be increased with the global optimum solution. The output obtained from the proposed SSO-based deep LSTM from the input video is the predicted path.

The steps involved in the algorithm of proposed SSO are as follows:

Algorithm 2: Spider Squirrel Optimization(SSO)
Input: Gradients, Input data, response, epochs
Output: Updated Gradients
Initialize Population, Gliding constant (Gl), Gliding distance (Ok)
while Termination criteria is not satisfied
    for each gradient element
        for 1 to Max_pop
            Updated weights are calculated using eq (10)
            Calculate optimisation_loss
        end for
        if Isoptimisation_loss minimum
            Updated Gradients = Updated weights
        end if
    end for
end while

5 Implementation

The implementation of the developed method is done in MATLAB tool using a PC with the Windows 10 OS, 8GB RAM, and Intel i3 core processor.

5.1 Camera specifications and position

The propsoed model have used two DSLR cameras as shown in Figure 3(a) and (b) using a standard tripod with the lenses shown in Figure 3(d).

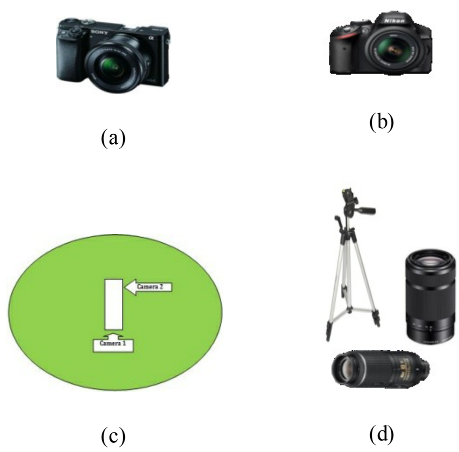


Fig. 3. a, b) Cameras used, c) Field view with cameras alignment and d) Lenses and Tripod

The first camera used is Nikon D3200 shown in Figure 3(b), size of the captured image is 1280x720 at the frame rate 60fps and used focal lengths-18mm to 55mm The other is Sony Alpha a6000 shown in Figure 3(a) which has 1920 x 1080 video resolution and number of frames per second or capture rate is 60fps and used focal lengths-55mm to 210 mm. These two cameras are placed in two different positions to get the play of batsmen i.e. in side view and front view. The cameras are placed approximately 1mtr high from the ground level and 22yards apart as shown in Figure 3(c).

5.2 Data Collection

As far as the observations made, there does not exist off-the-shelf datasets for evaluating the LBW decisions. Therefore, it is required to build a new dataset for this work. The propsoed research work has designed our own cricket LBW situation videos. The details are shown in Table 1. This work has captured around 80 videos at 60 fps in both the views.

Table 1. Dataset details.

	Front view	**Side View**
Frame(pixels)	1280x720	1920 x 1080
Capture rate	60fps	60fps
Number of videos	80	80
Key features	Pitching and impact	Bounce and height

The object in proposed datasets is a cricket ball with the specifications mentioned in [23]. The speed of the ball in the motion is approximately 35m/s to 60m/s used in taking the samples.

5.3 LBW Event Analysis

According to the cricket law 36 [24], the LBW out decision is analyzed by a sequence of events i.e. pitching, impact, and hitting of wickets. Using the proposed methodology which followed the cricket law 36, the LBW event analysis is carried out in the following sequence:

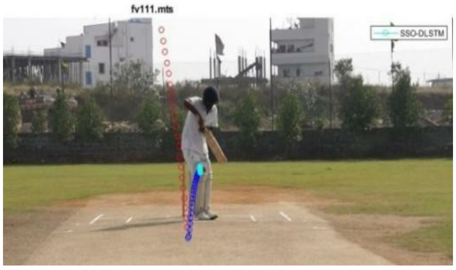
Cricket ball detection and tracking: From two different views, it has successfully detected and tracked the cricket ball using background subtraction and spatial tracking for finding the pitching and impact of the ball.

(a) (b)

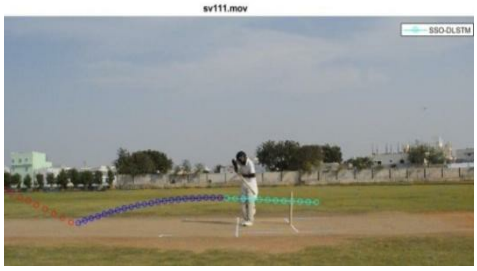
Fig. 4. a) Pitching and b) Impact

Here, front view video is considered for finding the pitching of the ball using algorithm 1 and the result is shown in Figure 4(a). If the pitching of the ball meets the condition, then we further analyze the video to find the impact of the ball using the same algorithm 1 and the result is shown in Figure 4(b).

Ball Path Prediction: After the sequential events i.e., pitching and impact of the ball meet the conditions then the path trajectory is estimated which is used to find whether or not the ball hits the wicket after the ball is intercepted by the batsman. Figure 5 below shows the predicted path in both the views using the proposed method.



(a)



(b)

Fig. 5. Path prediction in a) Front view and b) Side view

6 Results and Discussion

In this section, it disusses the event analysis results. As pitching and impact can be known in front view video, so the person at the front view camera acted as the umpire to make decisions about pitching and impact which are recorded manually.

The correctness means the ratio of similar decisions made by the umpire and proposed method to the sum of similar and conflicting decisions made by the umpire and proposed method.

$$Correctness = \frac{\#of\ similar\ decisions}{\#of\ similar + \#of\ conflicting\ decisions} \quad (11)$$

Table 2 shows the decisions of pitching and impact by the umpire are 90.6% and 87.5% accurate and by the proposed method are 97.3% and 97.5% accurate.

Table 2. Pitching and impact decisions in front view.

Total	**GT**	**Pitching Decision**		**GT**	**Impact Decision**	
		Umpire	**Proposed Method**		**Umpire**	**Proposed Method**
80	75	68	73	80	70	78

After the decisions of pitching and impact the decision of hitting wickets is taken by the two umpires positioned near the cameras on the field in both the views. The side view predicted path gives the height and movement of the ball beyond the impact point. Table 3 shows the result of hitting stumps decision by umpires and the proposed method in both views.

Table 3. Hitting decision

View	**Total**	**Hitting Decision**

		Umpire	Proposed Method	Correctness
Front	80	63	69	91.3%
Side	80	66	72	91.6%

From the total videos, the correctness of the decision taken by umpires obtained are 91.3% in front and 91.6% in side views using eq (11).

In Figure 6, the path predictions to find the hitting of wickets are shown which are obtained by running different algorithms like Kalman filter, DLSTM, and SSO based DLSTM.

(a) (b)

Fig. 6. Comparing with other methods a) Front view and b) Side View

The comparative analysis of trajectory prediction using the MSE parameter of different methods is depicted in Figure 7. If the path predicted is accurate then the decisions made based on ball locations can be accurate. When the training data percentage is 40, the MSE computed by Kalman Filter, deep LSTM, and the proposed model is 4.645, 3.434, and 2.142 respectively. For 80% training data, the MSE computed by Kalman Filter, deep LSTM, and the proposed model is 2.817, 1.317, and 1.107 respectively.

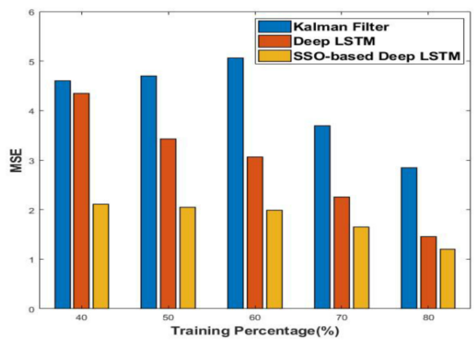


Fig. 7. Comparing with other methods a) Front view and b) Side View

6.1 Decision Analysis

After collecting the decisions from both the umpires and the proposed method, this decisions data is filtered and analyzed by the using predictive confidence-based deicision matrix. This matrix is used to find out the correctness of the umpire using eq (11). The decision matrix uses simple if else logic applied on data collected.

Table 4 shows final decisions taken by the umpire and proposed method about the LBW event whether the batsman is given out or not out. These decisions are taken on all videos in both the views, a total of 80 videos is obtained and out of which 63 and 66 are correct decisions made by umpire in front and side view respectively.

Table 4. Out decision

View	Total	Final Decision(out or not out)		
		Umpire	**Proposed Method**	**Correctness**
Front	80	63	69	91.3%
Side	80	66	72	91.6%

The experiment is carried out with the following limitation:

- As in updated cricket guidelines we have red, white, and pink color balls but we have experimented with red color balls only.

7 Conclusion

It is concluded that the proposed research work addresses the significant key issues of LBW decision making for umpires on the field. The straight umpire (front view) can take decisions about pitching and its impact using spatial tracking of the ball, where the leg umpire (side view) can analyze the bounce and hitting of wickets. For this, an effective path prediction method named SSO-based deep LSTM, which aims to predict the trajectory path from the video frames is proposed. The proposed method results with a MSE value of 1.107, when compared with other methods i.e., Kalman Filter and deep LSTM. This work provides performance statistics about batsmen, bowler, and umpire. The results have shown that the video visualization can provide cricket coaching with visually measurable and comparable summary records, and is thus an economical means for evaluating skill levels and examining the progress objectively and consistently. In the future, the system can be enhanced to automatically comment on the event occurred and generate sports news from the live commentary scripts.

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