A Machine Learning Framework for Shuttlecock Tracking and Player Service Fault Detection

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Data Analytics

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A Machine Learning Framework for Shuttlecock Tracking and Player Service Fault Detection

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Abstract

Shuttle Cock tracking is required for examining the trajectory of the shuttle cock. Player service fault analysis identifies service faults during badminton matches . The match point scored by players are analyzed by first referee through shuttle cock landing point and player service faults . If the first referee cannot make decision, they use technology such as a third umpire system to assist . The current challenge with the third umpire system is based on high number of marginal error for predicting match score . This research proposes a Machine Learning Framework to improve the accuracy of Shuttlecock Tracking and Player service Fault Detection . The proposed framework combines a shuttlecock trajectory model and a player service fault model . The shuttlecock trajectory model is implemented using Pre-trained Convolutional neural network (CNN) such as Tracknet.The player service fault model uses Google MediaPipe Pose Pre-trained CNN model to classify player service fault using Random Forest Classifier.The framework is trained using the Badminton world federation channel dataset.The dataset consist of 100000 images of badminton player and shuttle cock position ..The models are evaluated using a confusion matrix, loss,accuracy , precision , f1 and recall. The Optimised TrackNet Model has accuracy of 90% with less positioning error for shuttlecock tracking whereas Player service fault detection can classify player fault with 90% accuracy .The combined machine learning algorithm on shuttlecock tracking and player service fault would benefit Badminton World Federation (BWF) for enhancing match score analysis.
Keywords – CNN, Tracknet ,MediaPipe , Shuttle cock Tracking, Player service fault analysis

1 Introduction

Hawkeye is computer vision technology used in badminton sports to identify Shuttlecock Tracking , badminton Player action and player shot recognition.The Badminton being one of the fastest sports due to the speed of the shuttlecock which ranges from somehwere 480 to 493 km/h . However,due to the recent technical error of Hawkeye technology [1] in international Badminton matches resulted in Badminton world federation to rely on better technology than Hawkeye.

The increase in demand of Hawk eye spread across various sports such as cricket(Jayalath (2021)),tennis,basketball has proved usage of the computer vision technology to be most reliable due to human error such as refree and umpire

[1](https://bwfworldtour.bwfbadminton.com/news-single/2021/11/21/bwf-infront-pan-asia-and-hawk-eye-statement)

in other games.This technology uses Cross-matching the images taken by several cameras placed in various locations around the court or ground is how Hawk-Eye technology operates. Using triangulation, these cameras provide the system with images of the court from various angles. The technology may deliver film for instant replay using the same footage shot from several angles. Officials are able to see everything, including where the football, cricket ball, tennis ball, and shuttlecock projects and rest on the ground as all credit goes to various Sony hawk eye cameras.In the badminton sports the usage of the camera collect various pieces of video, which are then transmitted to a computer system that determines trajectory and positions as shown in Figure 1. With only a 3.6 mm margin of error, the computations result in a graphic that shows the exact location of a shuttlecock in real time as it was the reason of challenge as specified in above context.

The aim of this research is to track the trajectory of the Shuttlecock and detect Player Service Fault. The major contribution of this research is a novel machine learning framework that combines an shuttlecock trajectory model and player service fault model to improve referee decision making. A minor contribution of this research is a image dataset and body point landmark csv format dataset, which was generated from match video consist of player service fault detection images and body landmark stored in kaggle[2] repository .

In order to identify the optimal machine learning model this research compares pretrained Tracknet model Huang et al. (2019) with enhanced Tracknet model1 by optimising hyper parameters .To precisely place the badminton ball on the match footage, TrackNet model, a deep learning network based on heatmaps, is used.Whereas,The implemenation of the player service fault detection uses player pose estimation with reference to the badminton service fault.The service fault detection uses Mediapipe pose and holistic model to train body landmark coordinates with Random forest classifier and Knn Classifier.A machine learning (ML) method called MediaPipe PoseZhang et al. (2020) uses RGB video frames to infer 33 3D landmarks and a background segmentation mask on the entire body.Using RGB video frames, the MediaPipe Pose machine learning (ML) technique infers 33 3D landmarks and a backdrop segmentation mask on the full body.Whereas, Mediapipe Holistic model uses 543 landmarks (33 pose landmarks, 468 face landmarks, and 21 hand landmarks per hand), Based on accuracy,precision, loss, latency and size,our research objective has been satisfied to analyse the application of machine learning framework on shuttlecock tracking and player service fault detection.

This paper discusses machine learning models used for tracking of the shuttlecock and player posture analysis in section 2 related work . The research methodology is discussed in section 3. Section 4 discusses the design components for the shuttlecock trajectory and player fault analysis machine learning framework for Badminton decision review system. The implementation of this research is discussed in section 5. Section 6 presents and discusses the evaluation results. Section 7 concludes the research and discusses future work.

[2]https://www.kaggle.com/datasets/axeireland/body-keypoint-landmark-coordinates-dataset

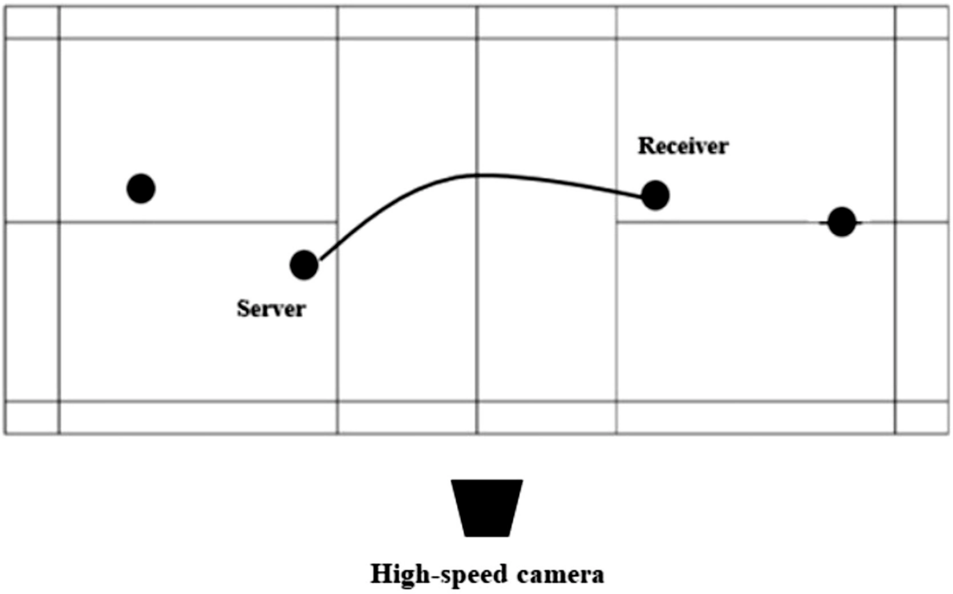

Figure 1: Hawk Eye Camera Position

2 Related Work

The use of computer vision technology in sports has been used by referee in each individual sports including Badminton to progress in sports analysis sector as mentioned in Thomas et al. (2017).

The ball trajectory algorithm has derived from various sports such as in table tennis and tennis by Zhao et al. (2018), Shishido et al. (2013),Reno et al. (2018) used temporal and spatial correlations to detect fast motion of the ball using Kalman filter which was ineffective due to occlusion with 74% accuracy.

However,in the field of badminton the badminton robotChen et al. (2016),Cao et al. (2021),Chen et al. (2021) in competitive game revolutionize the shuttlecock tracking and line detection concept in sports using YOLOv4 network which has precision of 88.39% when compared to SF-YOLOV4 . A similar research by Chen et al. (2019) used FTOC method to track shuttlecock in badminton using AdaBoost Algorithm which can be trained using OpenCV Library as well as Vrajesh et al. (2020) used YOLOv3 achieved an average with precision accuracy of 94.52% with 10.65 fps respectively in but as its not cost efficient video analysis should be right approach .

Hence, due to the fast image processing time the solution would rely on deep learning model using CNN algorithm independent of instrument usage.Firstly,.Hence, the usage of SOTA (State Of The art Algorithm) Lee (2016) may not be appropriate algorithm for shuttlecock tracking instead our research will adapt the usage of a convolutional neural network (CNN) based framework, called TrackNet Huang et al. (2019) a pre-trained deep learning model which provides precision of 85% from 2018 database of Indonesia open from YouTube channel which resulted in total number of frames of 18, 242,through this algorithm the Ball Detection Heatmap for the most recent frame is produced by the TrackNet algorithm which is a combination of VggNet-16 and Deconvolutional Neural network (Deconvnet).The trackNet Model seems to be fit in our research work but we may need better enhanced model approach as it will be used in real-time scenario to identify shuttlecock trajectory.

The further research as referred in Zhu et al. (2022) with computer virtuality on human posture estimation doesn't quantity robust approach when compared to research work in Host and Ivašić-Kos (2022) focused on using HAR (human action recognition), which mostly used deep learning techniques based on CNN and LSTM. The usage of deep learning model such as convolutional Neural Network has been evolving in the field of Badminton. The usage of such algorithm in image processing doesn't need processing phase as mentioned in research paper by Rahmad et al. (2018) as well as Besides CNN, second model for supervised deep learning is recurrent neural network (RNN) model and one of the common RNN model is called Long Short-Term Memory with accuracy of 92% and binti Rahmad et al. (2019) suggest evaluation of different pre-trained deep CNN models such as GoogleNet model which has the highest classification and accuracy of 87.5% when compared to AlexNet,VggNet-16, and VggNet-19 in which justifies high accuracy for pose recognition with limitation of GPU usage which can effect processing time. Ibrahim et al. (2020) used Images from badminton matches in two classes—hit and non-hit action—make up the data inputs and trained using pre-trained AlexNet CNN model obtained 98.7% accuracy of classification.

Liu and Liang (2022) suggests usage of video analysis instead of sensor based approach to triples of new skeleton relations, a partial update mechanism is employed to dynamically generate a human skeleton topology map, and a Graph convolutional Neural network -based skeleton action recognition method is used to achieve action recognition. Experimental results demonstrate that the suggested method achieves 63 %, 84 %, and 92%, respectively, recognition accuracy on multiple benchmark datasets, enhancing the accuracy of human hitting action recognition. The player bounding box and skeleton are detected using YOLOv3 Cao et al. (2021) and OpenPose skeletal imaging through Cao et al. (2017).In our research the motive is to predict player service fault detection which can be achieved when single or multiplayer pose estimation is recorded .The Openpose package along with Yolov3 detect all human frame which are not required hence we have used Google Mediapipe model Mediapipe pose and holistic to detect service fault from player .Similar to our research the mediapipe model has been utilized in Cabo et al. (n.d.) and Jothika Sunney (n.d.) martial art pose and Yoga Poses classification with 95% accuracy using XgBoost.

In conclusion, the state of the art indicates that several models such as AlexNet, GoogleNet, VggNet-16, and VggNet-19 is used in the shuttlecock tracking out of which Tracknet badminton algorithm have been improved and there is a need through experimentation to identify the optimal model for use in finding shuttlecock trajectory. On the other hand ,Current research indicates that deep learning models can be optimised using CNN architecture for detection of Human Activity Recognition . The pose estimation are important for analyzing player's service fault action in the badminton court .The 3D skeleton imaging are possible using body landmark model which is media pipe and open pose package .But,Since we are aiming to detection only player action and removing other human pose of the frame due to which implementation of the Google Mediapipe model is suitable for our research work which generate 33 body keypoint landmark for pose detection.

3 Methodology

The research methodology consists of five steps namely data gathering, data pre-processing, data transformation, data modelling , evaluation and results as shown in Fig. 2. **The first phase** of the research methodology illustrates *Data Gathering*

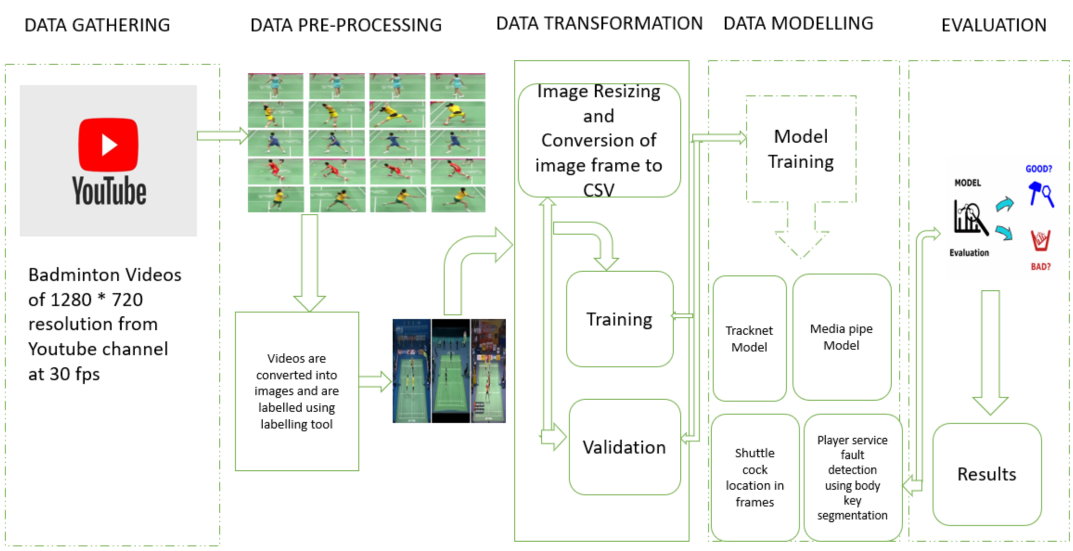

Figure 2: Research methodology

which is outline of how the data acquisition task will work .Whereas, in this research it has retrieved dataset from public data of BWF TV channel in youtube database .A badminton match can usually last for an hour and the video may have generate nearly 100,000 frames in the form of raw data.This research have used badminton match video data[3] from Yonex All England Open Championship BWF Super 1000 2018 of women singles between TAI Tzu Ying (TPE) vs Akane YAMAGUCHI (JPN) —.The Video is scrapped for first 7 minutes of the rally generating 12,180 frames with resolution of 1280 × 720 at a the frame rate of 30 fps.The 7 minute video was further divided into 12 video each ranging from 5 sec to 20 sec.For training model we have utilized 5 sec video .Whereas, The player service fault model uses video dataset[4] from BWF Development youtube channel with relevant frame of 280 .

The **The second step** ,*Data Pre-processing* involves conversion of the video into images for the data generation .The images are then resized from 1280*720 images to 512*288.In the case of shuttlecock trajectory the resized images undergoes labelling procedure and for the same this research have used Microsoft's visual object tagging tool which provides location of the shuttlecock in each frame and the details of the shuttlecock coordinates are recorded in CSV format which is used for data transformation and model training .The labelled images are converted into heat map in Fig 3. annotted images to find the ground truth of the positioning of the shuttlecock in each frame using Gaussian distribution.In the case for Player service fault detection the badminton video undergoes resizing after conversion into images and each images are classified according to the key body landmark point which will be used for classification in further steps of the methodology. The result

[3]https://youtu.be/PCyNbtMVkpI
[4]https://youtu.be/LFv8qezrj-Y

of the pre-processing generated labelled and resized images of shuttle location as 156 image in PNG format and Player pose estimation has 132 relevant images .The 156 images of the shuttlecock location are converted into CSV format which has details of frame, The attributes "Frame Name," "Visibility Class," "X," and "Y" are assigned to each frame. In the shuttlecock tracking dataset, "Visibility Class" is divided into the V C = 0 and V C = 1 categories. If V C is equal to 0, the ball is outside of the frame, and if it is equal to 1, it is inside the frame.

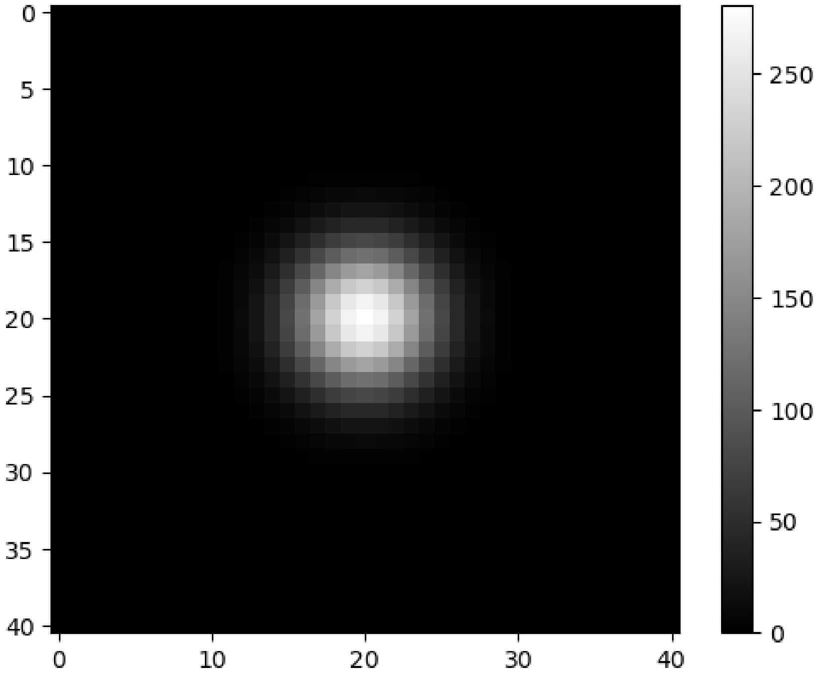

Figure 3: Detection Heat Map

The Data preprocessing of player service fault entails skeletonizing the badminton video or image dataset and then using the Mediapipe pose estimation model shown in Fig .3 to feature extract 33 3D landmark points in the x, y, and z axes. 33 3D landmarks are available in a single image frame using Mediapipe posture. Figure 4 displays the 33 landmark sites that the Mediapipe posture model identified. The 33 landmark locations as shown in Fig 5. has x, y, and z coordinates served as the basis for estimating the player service fault pose. First, the OpenCV library was used to read the image. While Mediapipe pose requires RGB input, OpenCV can read data in BGR format. The image was initially preprocessed by changing it from BGR to RGB.

The **The third step**, *Data Transformation* n involves labelled image data set of shuttlecock trajectory and body keypoint dataset of badminton player for service fault pose estimation which is in csv format undergoes data transformation to form train and test dataset. In the case of Shuttle cock Trajectory framework ,the ground truth heat map was created through Gaussian distribution function which has shuttle cock detection location in the black and white image form which saves data with PNG image format .The heat map as ground truth involves positioning of the shuttlecock in the frame which results in 70% training Data and 30% validation which generates 109 training images and 47 testing images . Whereas, for player service fault framework draws body landmark with key points which is in the form of

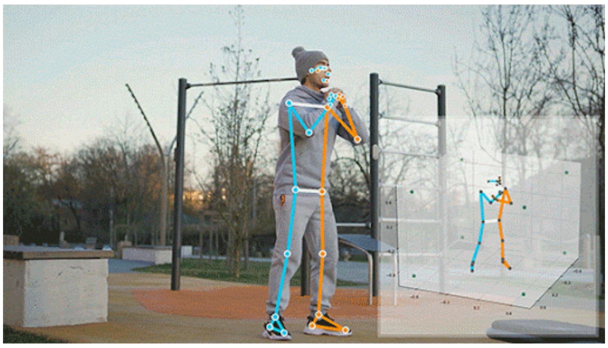

Figure 4: Mediapipe Pose Model

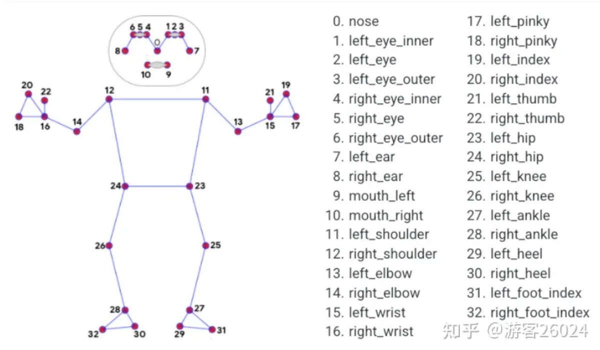

Figure 5: 33 Body Landmark

X,Y,Z,visibility where X,Y,Z are the coordinates of the each pose with visibility as probability of landmark captured from each frame.The data captured was converted to array in the form of keypoints for body pose, ,knee,foot and ankle .The data transformation seperates data into class variable and body landmark .The class variable are estimation of player service fault which is categorized into "Not Foul" and "Foot Not Stationary" which was later label encoded .The body landmark consist of keypoints of each class.The data was split into 70:30 ratio train and test data before applying classification.

The **The fourth step**, *Data Modelling* involves model training and implementation of the model. The shuttlecock tracking framework were trained by splitting dataset of 156 images with Training image as 109 and Testing images as 47 used for validation. Tracknet Huang et al. (2019) models as shown in Fig 6. for pre-trained transfer learning were employed in this study. It is an FCN model that uses VGG16 to produce the feature map and DeconvNet to decode utilizing classification of the pixels. Multiple consecutive frames could be used as input for TrackNet, and the model will learn not only object tracking but also trajectory to improve its placement and recognition abilities. Gaussian heat maps centered on the ball will be generated by TrackNet to show the ball's location. To calculate the difference between the heat map of the prediction and the ground truth, categorical cross-entropy is utilized as the loss function. TrackNet were trained with an image shape of (256,288,512). To predict the model weight to be used retraining were trained with 30 epochs, categorical cross-entropy loss function, ReLU activation function and SoftMax activation function and tolerance were utilized. The models were optimized using Ada delta optimizer as well as some of the parameters such as learning rate,batch size and epoch value are optimized during further retraining of model.In the case of player service fault model involves training of the body landmark data frame perceived through mediapipe pose model and evaluating through three classification model "Random Forest,Support vector machine (SVM) and Decision tree".The performance of the model is considered to be good fit based on evaluation matrix which is used for predicting player service fault.

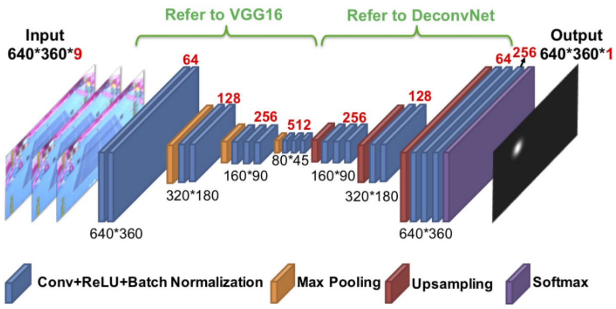

Figure 6: TrackNet Architecture

The fifth step,*Evaluation and Results* involves evaluating the performance of the shuttlecock tracking model and player service fault detection model.The shuttlecock tracking model is evaluated using accuracy,precision ,recall with 10-fold cross validation and PE (Positioning Error) score which is used as metric to verify percentage of shuttle cock postion error between two model of Tracknet.Similarly,by evaluating accuracy , precision and recall Random forest classifier seems to be suitable for player service fault prediction.

4 Design Specification

The Badminton Decision system **architecture** combines combines Shuttlecock tracking machine learning framework and Player service fault detection machine learning framework as shown in Fig. 7. **The components of** the Shuttlecock Tracking Model include Badminton Youtube Video,image labelling ,Heat map image and pre-trained TrackNet model as discussed in section 4.1. Components of the Player Service Fault Detection Model are discussed in section 4.2.

4.1 Shuttlecock Tracking Model

The Shuttlecock tracking machine learning framework is initiated through dataset in the form of badminton match video gathered from Youtube of BWF channel.The initial resolution of the video was 1280 * 720. with a frame rate of 30fps.The OpenCV library has been utilized to convert and read video frame to images.The input images labelled which generated coordinates of the shuttlecock in the frame .The labelled images are annotated by converting into heat map to find relative with ground truth .After extracting the annotated images along with labelled image the dataset undergoes train and test compilation to be applied on pre-trained CNN model know as TrackNet.The training of the Tracknet model with epoch,classes,load weight and batch size create saved weight which will be used to retrain the model and compare 2 model.The model fit is evaluated on the basis of accuracy ,precision

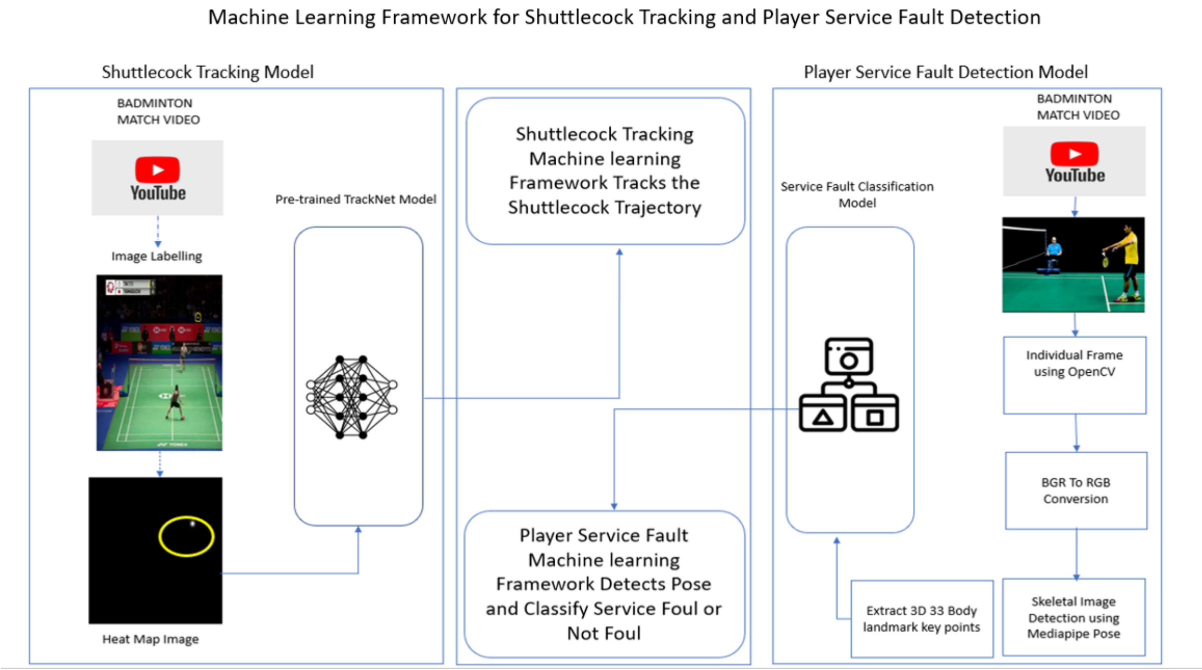

Figure 7: Badminton Decision System Architecture

,recall and positioning error (PE) in pixels.Our system architecture model has less position error which is deemed as better model for shuttlecock tracking.

4.2 Player Service Fault Detection Model

The player Service fault Detection framework initiates through video dataset from BWF development Youtube channel.The video was downloaded with 1280*720 resolution running at 25.8 fps.The research work uses OpenCV library to read each frame from the video.Each frame is converted from BGR to RGB and then it was ingested into the Google Mediapipe pose model.The pose model detect body landmark with 33 keypoint.This player detection model focuses on service fault attempted by badminton player for which it calculates angle between lower body part such as left leg using keypoints.The landmark coordinates detects two classes of the pose estimation i.e. "FOOT NOT STATIONARY" and "NOT FOUL". The 33 3D landmark coordinates are flattened and data transformed into csv format and later during data frame development class variable or categorical variable which is "NOT FOUL" and "FOOT NOT STATIONARY" are label encoded.The collected landmark coordinate are ingested into Machine learning classifier such as Random Forest ,SVM and Decision tree from which random classifier saved model has highest accuracy with better prediction for service fault by player in badminton court.

5 Implementation

The Machine Learning Framework for shuttlecock tracking and Player Service Fault detection were **implemented** on Jupyter notebook along with google colab notebook with python version 3.9 on device having configuration Intel(R) Core(TM) i5-1035G1 CPU @ 1.00GHz 1.19 GHz with 8 GB Ram .The Shuttlecock tracking model was implemented using following python libraries argparse,numpy,matplotlib, pillow,h5py,pydot,keras,tensorflow and opencv-python, CUDA 9.0 and cuDNN 7.0 for PyTorch (GPU) python libraries on google colab notebook with GPU storage of 12 GB RAM and disk capacity of 78 GB as well as some part of the script were implemented on jupyter notbook with device configuration of 8gb ram. The model was trained using dataset collected in the form of video of 4972 frame from Youtube Badminton Channel.Hence,we are using video of worth 15s which has 157 image frame read through OpenCV library .The collected image frame are labelled using Microsoft Visual Object Tagging Tool which provides output in csv format. The labelled images are used for Ground truth and heat map prediction following which Training and testing of model was performed with 70:30 ratio.The train and test images utilises keras library with tensorflow-cpu backend to train Tracknet Model.In order to optimize weights of the network, the Adadelta optimizer is applied. The key parameters such as learning rate,batch size,steps per epoch,epoch and initial weight were modified. To compare the performance of TrackNet frameworks with one input frame and three consecutive input frames, two versions of TrackNet are implemented. For convenience, TrackNet that takes one input frame is named as Model 2 and TrackNet that takes three consecutive input frames is named as Model 2 both model were evaluated using Accuracy ,Precision and Recall evaluation and best model fit were Model 2 due to the less number of positioning error.The estimation of the model 2 predicts tracking of the shuttlecock as shown in the Fig. 8 and Fig.9 .

Figure 8: Shuttlecock Trajectory 1st Frame

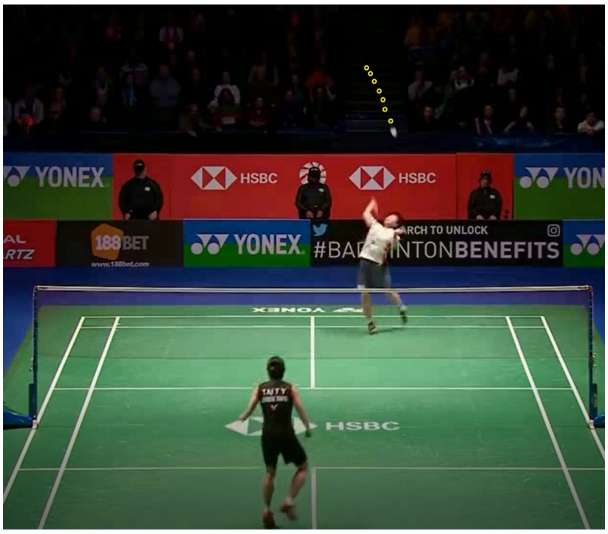

Figure 9: Shuttlecock Trajectory 2nd Frame

On the other hand , the Player Service Fault detection machine learning model was implemented using Mediapipe pose model,OpenCV,Numpy and SKlearn.The Model was trained using publicly available dataset in the form of video from Youtube Badminton development channel.The motive of the player service fault detection model was to detect service foul attempted by player which mediapipe pose model was implemented on badminton video consisting of 132 frames .The mediapipe pose model creates 33 3D body landmark on each frame.We used angle calculation logic on the left leg landmark point consist of knee,foot and heel.The body landmarks keypoints of the calculates angle were saved in data frame which was later divided into 70:30 ratio training and testing.The training and test model were later evaluated using machine learning classifier.The best fit was random forest classifier which achieved highest accuracy to validate service foul detection using pose estimation of the player.

6 Evaluation

This sections illustrates research conducted on the two machine learning framework . Section 1 evaluates performance of the shuttlecock tracking and section 2 evaluates performance of the Player service fault detection .

6.1 Performance of the Shuttlcock Tracking Model

The Aim of the first experiment was to analyze to what extent machine learning methodology could track shuttlecock trajectory.The key parameter to evaluate is the accuracy,precision ,recall which are optimized by enhancing Learning rate 1.0 ,Batch size 2,Steps per epoch 200,epochs 30 and Initial weights.As per the first experiment the trackNet MOdel was implemented on first frame with learning rate as 1.0 ,n=clasess , batch size and steps per epoch which detects shuttlecock trajectory with accuracy ,precision and Recall as 85.0%, 57.7%, and 68.7% respectively. The researchers in Huang et al. (2019) focuses on training of one image per frame which can cause occlusion .Hence, table below shows the comparison of the TrackNet model 1 using one frame to train which was used by previous researches abd our model which was TrackNet 2 model uses three consecutive image to train Tracknet model .Hence , The accuracy of the Tracknet 2 Model is having higher accuracy,precision and Recall than TrackNet Model 1 with 90%,97%,92%.

6.2 Model Comparison on Positioning Error

The prediction details of TrackNet Model 1 and Model 2 is shown in Figure 10. with respect to the positioning error. TrackNet Model 2 and TrackNet Model 1 evaluation is based on TP, FP, TN, and FN which stand for true positive, false positive, true negative, and false negative, respectively. The "Visibility Class" is the key feature in predicting False Positive or False negative in the image frame .The Visibility class consist of VC1,VC2 AND VC3 where False Positive justifies PE(Positioning Error) is greater than 7.5 pixels where False negative in justifies no shuttlecock detected or more than one shuttlecock detected when there is only shuttlecock in the frame.The Positioning error graph illustrates percentage of error opted by two models while detecting shuttlecock in the frame.The TrackNet Model 2 seems having less error positioning with 0.28% of the error margin which justifies can detect occlusion in the frame also have ability to use neighbouring image frame for shuttlecock detection .The evaluation of the metrics is based on precision ,recall and F-1 score as shown in Fig 11.

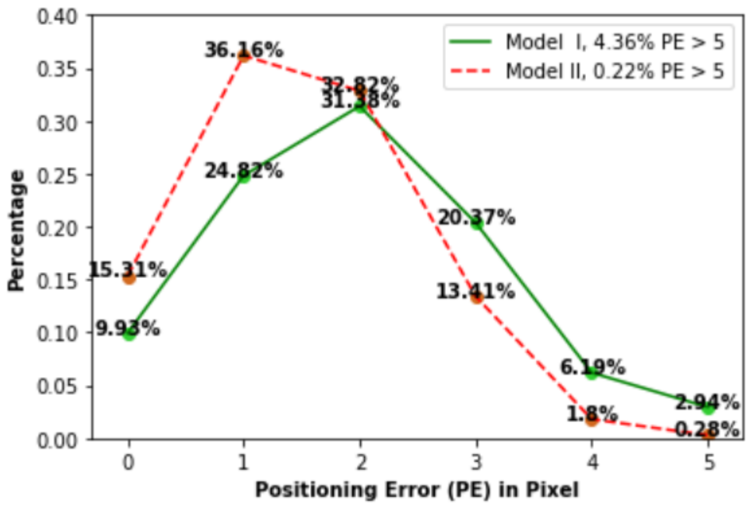

Figure 10: TrackNet Model Positioning Error

6.3 Model Performance and Comparison of Player Service Fault Detection

The aim of the experiment on Player service Fault Detection frameworks compares the performance of different Machine Learning algorithms on 3D body landmark dataset. Three Machine learning models Decision tree, SVM and Random Forest were analyzed based on . Figure.5 shows the comparison of different classifier models based on ROC curve of the three models. The AUC of the random forest classifier has the highest score when compared to the other two models as shown in Fig 12.The accuracy score when compared to the three model Random forest

$$
\begin{aligned}
\text{Precision} &= \frac{\text{\# of True Positive}}{\text{\# of True Positive + False Positive}}, \\
\text{Recall} &= \frac{\text{\# of True Positive}}{\text{\# of VC1+VC2+VC3}}, \, and \\
\text{F1-measure} &= \frac{2(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}.
\end{aligned}
$$

Figure 11: Precision,Recall and F-1 SCORE

classifier stand out with 90% accuracy followed by decision tree and SVC .The Random forest classifier is used to develop and save model which will be used to predict outcome of the player service fault detection model. The prediction of the

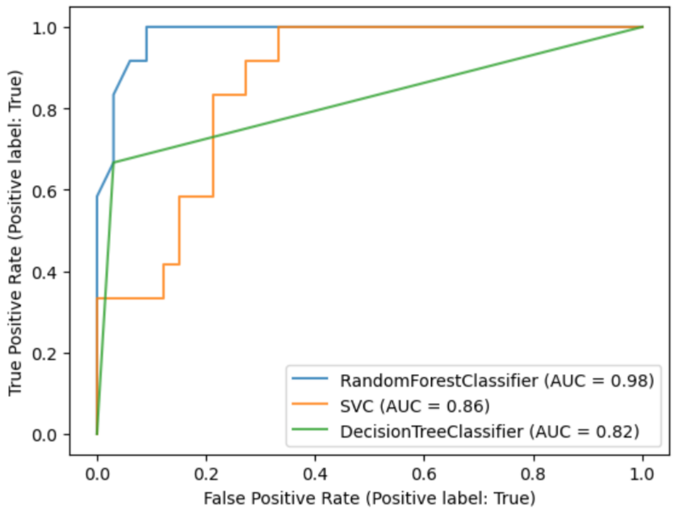

Figure 12: ROC Curve Display of Model

output post classifying random forest classifier model produces predicted output of the player attempting ”FOOT NOT STATIONARY” service foul and has been detected with accuracy as shown in Fig 13.

One of the major challenge faces during research work is to gather data which is relevant to the project. In the case of Player service fault detection the relevant dataset was unavailable hence we need to create dataset by scrapping video frame from YouTube channel and post converting frames into CSV which has relevant training body landmarks used for predicting model.Whereas,while comparing with shuttlecock tracking model occlusion in the video frame was a challenge which eventually prompted to use multiple frames from training causing high amount of the CPU and GPU usage .In the real time scenario the shuttle cock tracking model need to be tuned a bit further as well as Player service fault detection framework.

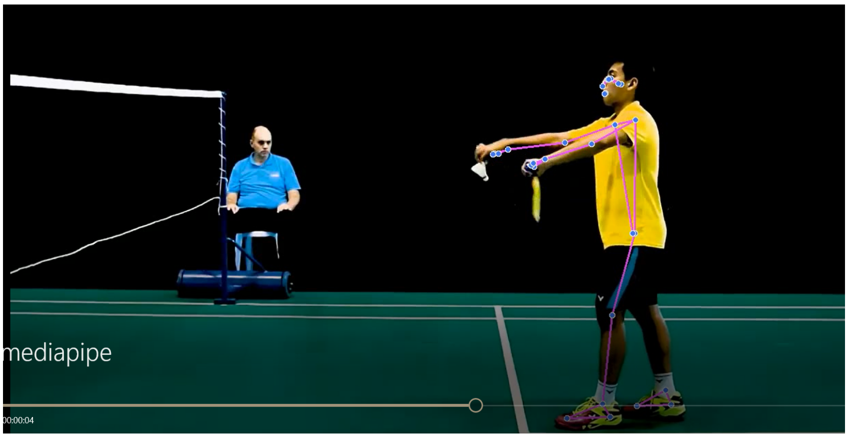

Figure 13: NOT FOUL

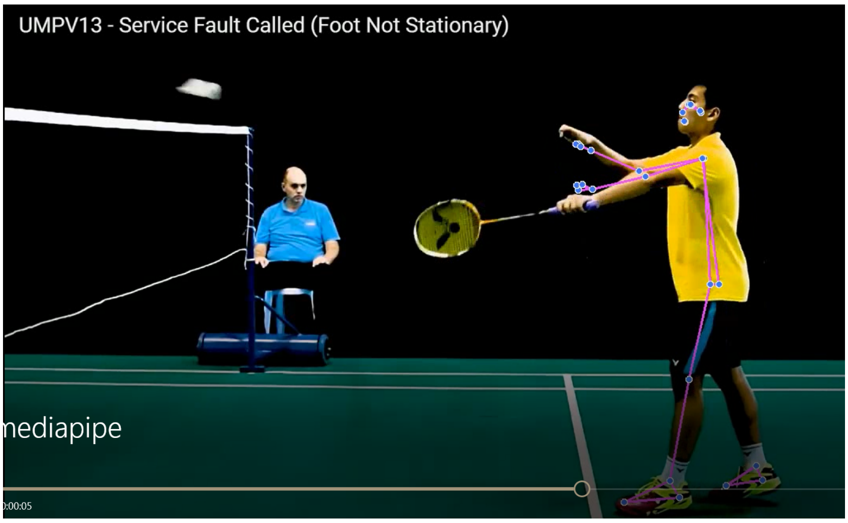

Figure 14: FOOT NOT STATIONARY

7 Conclusion and Future Work

The aim of this research is to track the trajectory of the Shuttlecock and detect Player Service Fault for referees .The decision system combines of shuttlecock tracking model which would be helpful for predicting path and location of shuttlecock from projectile to landing on ground.The badminton technical official currently uses HAWK eye camera technology to detect shuttlecock placement but since it has marginal error which has caused technical official and players to review outcome of the match in a critical way .The shuttlecock tracking model generated by us knows as TrackNet Model 2 has been by optimised by modifying the hyper-parameters function and using three frame which resulted in accuracy score of 90% which better than other SOTA algorithm for shuttlecock tracking as well as the player service fault detection model used Google Mediapipe pose model to generate 3D body landmark which was used for predicting Service fault from video for which we trained data with random forest classifier which in turn provided accuracy of 90% compared to other model which seems better fit as service fault detection has not been implemented so hence there is a scope of advancement and research work on such module.The Research with the aim on quantify badminton game such as shuttlecock tracking and player service detection has a scope of implementing in real time scenario as more research as future work is needed to increase accuracy of the shuttlecock being fastest ball among all games as well as for service fault detection multiple service fault with multiplayer action detection would be scope of work being predicted .

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