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Exploring Team Passing and Movement in Sports: A Deep Learning Framework

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Abstract

Sports are a type of competitive physical activity that aims to promote the actual abilities and capacity of a person based on team and player performance. The main agenda of a team in sports is to achieve a better score when compared to their opponent team. During this play period, the defensive players further try to predict the upcoming moves of the attackers to prevent them from scoring goals and vice versa. Such action is an outstanding illustration of a predictable nature and is a key part of human intelligence. In this way, the consistently developing interests in sports have paved the way for the development of various analytical methods and techniques to understand the boundaries of sports. Recent advances in deep learning algorithms have shown a way for many effective and successful applications. This proposed work aims to devise a novel system that is an integration of classification and CNN-based DenseNet framework for predicting the next move of a player based on the player's attitude and body movements in a sport. The proposed model showed better accuracy compared to other classification models. Similarly, numerous existing problems in the field of mining, metal and fuel industries can be addressed with the support of advanced technologies like AI and CV. The CNN-based models and computer vision techniques can be used in mining industries to forecast blast-induced air-blast overpressure in open pit mines and also to distinguish the source area of microseismic occasions based on recorded ground tremors, therefore preventing mine catastrophe. Nevertheless, not only on-site but also the usage of multiple deep learning hybrid and detection algorithms helps in reducing irregularities and faults at manufacturing units with an increase in automation process and smart manufacturing techniques.

Keywords: *ComputerVision, Convolutional Neural Network (CNN), DenseNet161, ResNet152.*

1.0 Introduction

A football game is one of the main sports in the team sports family. It involves various actions of attacking, defending, and kicking a ball to score a goal. The two teams compete with each other to get the ball into the other opponent's goal. Statistical Football prediction is a method used in football sports betting that predicts the results of the matches with the aid of statistical tools. This is to outperform the predictions, which utilise them to set better odds on the outcome of football matches. The study explores how passing network and positioning variables can help in football sport[1]. Deep learning models are being used extensively to solve various problems related to the metal extraction phase, mining exploration phases etc., such as equipment and mine safety, equipment management w.r.t loading and unloading materials[2].

Machine learning and Deep Learning have developed with enormous information technologies and computer vision technologies that have paved the way for many new chances for data-intensive science in the sports domain. Deep learning is used in video segmentation, player detection and action/move recognition which are crucial in sports video analysis. Deep Learning (DL) framework

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performs phenomenally well in body posture and gesture recognition which aids in the game analysis. Predicting the next move of a player in a game is quite a challenging task. This plays a major role in the opponent team's success. The study makes use of video of sports to extract continuous images and analyse the images for prediction. Image detection technologies such as object capture, target recognition, edge detection and grayscale image processing are used to achieve the needs for sports image detection[3]. The model uses the computational method for the classification of images and pattern recognition and draws the inference out of predicted results[4]. Previously the work used direct counter-attacking tactics that use notational analysis but this method is not effective for balanced defenses. The bill should be passed by evaluating the quality of the pass and considering the effect of the pass on opposition. Thus, the proposed work aims to devise a novel system that is an integration of computer vision technology and CNN-based DenseNet framework for predicting the next move of a player through supervised learning where the images are classified based on his/her attitude and body movements in a sport. Computer Vision technology is utilised to improve the quality of images. The system assists mentors and coaches to examine the game methodology/ strategy which is valuable for the forthcoming matches/ games. Machine Learning (ML) can be applied for the automatic detection of any complex multi-player behaviour in the game. The team's activity is analysed by identifying the main key elements of any play[5]. The paper depicts how sports will benefit from deep learning and computer vision technologies. By applying deep learning technologies, we can provide rich suggestions and insights to sports persons, trainers and coaches for gameplay and action.

The works dissected were classified as DL framework for sports result prediction, computer vision in sports that includes camera calibration and tracking, and ball and player tracking to predict the next move of the player. The proposed work aims to predict the next move of the player in football based on the pre-trained model that takes body movement and attitude of the player into consideration, one of the most significant topics in sports aids in success estimation and planning of game strategy beforehand.

2.0 Literature Survey

The literature survey presents an exhaustive survey of examination focused on the applications of deep learning, computer vision and its applications in the field of sports. The works dissected were classified as DL framework for sports result prediction, computer vision in sports that includes camera calibration and tracking, and ball and player tracking to predict the next move of the player. We have chosen the following papers based on their relevance to our problem statement. The methodologies that inspired are as follows:

The study analyses a variety of currently used computer vision commercial applications in the domain of sports analysis. There exist several well-established commercial applications using technologies like multi-camera ball tracking to provide in-depth data for coaching, refereeing decision making and live analysis for TV viewers. Vision-based tracking systems for broadcast cameras function by placing overlays in the image. Player tracking applications for tactical analysis and training generally rely on semi-automated approaches where operators are active in initialising and correcting vision-based tracking systems. Bianco *et al.*,[6] has successfully highlighted some of the current uses of computer vision in sports and discussed various CNN architectures like VGG, AlexNet, GoogLeNet, Batch Normalisation etc. SE-ResNeXt-50 has also achieved high accuracy. Panna *et al.*,[7] has developed a framework for predicting players' next move. The authors have used water polo and basketball datasets and compared the predictions with the proposed method. Sports videos have been analysed for tracking players and balls[8]. In this paper, the Deep Neural Network (DNN) based approach is used for the automatic detection of jersey numbers from soccer videos. Different ways of encoding schemes are used to identify every number as a separate class.

Gonçalves *et al.*,[9] explores passing network and positioning variables. The closeness and betweenness scores of the players in the team passing network were computed and represented. The computation is based on a matrix and the closeness score indicates the passing ball among teammates. Between scores of players act as a connecting bridge. Positioning relations are based on positional coordinators from the players[10].

The proposed sport result prediction in [11] uses a smart CRISP-DM (Cross Industry Standard Process for Data Mining) framework with six steps, based on the steps of CRISP-DM. Domain understanding of the nuances of the sport and data understanding where the granularity of the data to be retrieved is decided from the source data, Data

processing and feature extraction are used to identify the most important variables and they are preprocessed by summing up in-play variable per match per team modelling. Based on surveys the train and test datasets are chosen and experimented using a range of machine-selected and human-selected feature sets. Therefore, the study proposed a novel sports prediction framework that uses ML-based Artificial Neural Network (ANN) as a learning strategy.

In [8] a framework of generic type for predicting future events in sports videos from visual inputs directly is developed using water polo and basketball datasets and they are used for comparing the predictions of the proposed methodology. The following steps are performed in dividing original datasets into train and test sets. The setting of general benchmarks for both games, player tracking and overhead projection is performed to obtain an overhead view from the image view. The next location of the ball in water polo is predicted with Fully Convolutional Network (FCN) and Visual Geometry Group (VGG)16 as the backbone system in which FCN shows drawbacks based on the amount of data. Where the ball will be next in the case of water polo is estimated using early fusion and late fusion. The accuracy of the model on basketball was 69.9% and on water polo about 36.8%. The performance in a model trained directly on water polo (which achieves 45.5%) is better than the performance in water polo but the same as the most open teammate baseline with 36.7% accuracy.

In [6] various benchmarking architectures are taken into consideration including AlexNet, DenseNet, VGG19, ResNet and NASNet. The models that are trained using the PyTorch framework and deep learning frameworks are collected. For efficient benchmark analysis, various useful performance indices for DNN models are chosen. The used indices are accuracy rate, model complexity, memory usage, inference time, computational complexity etc. The key findings of [6] are increase in the number of operations is not proportional to an increase in recognition accuracy. The SE-ResNeXt-50 (32x4d) shows a very high accuracy despite a lesser number of operations. Addition of interactive plots to the repository to examine the results of the study more extensively and also effortlessly be able to add new entries. The paper describes a deep convolution neural network-based methodology for overcoming the problem with the automatic recognition of jersey numbers from soccer videos. It was used for subsequent automatic player identification together with knowledge about the teams and the jersey number of their respective players. They compared and presented the two vector encoding schemes: Semi-automatic labelling with automatic player detection based on Histogram of Oriented Gradients (HOG) that is combined with a linear Support Vector Machine (SVM)-Deep Convolutional Neural Network made up of three convolutional layers, each of these is succeeded by a max-pooling layer along with a ReLU unit along with the three fully connected hidden layers with optional dropout layers and followed by a SoftMax loss layer.

This paper uses a sports video dataset to extract continuous streaming images to analyse and predict the movement of players and predict winning teams[11]. Image detection technology like edge detection, grayscale processing etc. is used[12]. Sensors are used in real-time to collect human motion data. It needs to have a strong computation power for data preprocessing, model training and recognition. The focus of the football players is determined using various factors like- relevant data for football players movement detection and prediction, the difference between actual match play and training, difference between players' behaviour between youth and elite.

The dataset of images is collected and the CNN model is applied to different types of sports data such as football, baseball, gymnastics and hockey and the accuracy is compared by varying optimisers[13]. The Stochastic Gradient Descent (SGD) optimiser for the ResNet model has shown better accuracy for all sports[14]. DL models have shown improved results in mineral processing automation and mining. In a sequence of operations such as drilling and blasting, CNN models have been used to evaluate the strength and friction.

3.0 Materials and Method

Predicting the next move of a player in a game is quite a challenging task. This plays a major role in the opponent team's success. The system aims to perform a comparative study of predictions that use DenseNet and ResNet as the backbone. The main objective is to pre-classify the dataset based on the emotion, attitude and body movements of the player as seen from the image of the football match video clip. Using super-resolution, a computer vision technique is used to enhance the resolution of an image to predict the next movement of the football player. Performance

analysis and comparative study are conducted with other models.

3.1 Super-Resolution

Enhanced Deep Super-Resolution Network (EDSR) is used to improve the quality of images by upscaling the images by 4 times the resolution power. EDSR has a ResNet architecture but it does not contain the batch normalisation layers and residual blocks are not followed by ReLu activation layers. Batch normalisation layers have been avoided to obtain a greater range of flexibility from the feature networks and also it saves the Graphics Processing Unit (GPU) memory usage by 40%. However, this causes instability in large models, to counter that residual scaling a factor of 0.1 in each residual block is being utilised. These scaling layers are placed after the last convolution layers. Selection of the best feature in the dataset for the prediction is a challenging task. Most of the research around 65% studies considered ANN as their best predictive model in sports with 92% accuracy. Decision trees were the second most commonly used model for prediction[15].

The proposed model in this study uses the CNN-based approach DenseNet and ResNet which shows better accuracy with 98% when compared to ANN models[16]. The paper tries to identify explanatory variables that predict the probable winning team. The attributes required in the dataset include tournament series, court, dates of the match, location and ranking of winners and losers in the match. The ML models are used such as Logistic Regression (LR), Neural Network (NN), Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosting Machine (GBM). LR shows an accuracy of 0.703, the NN model shows an accuracy of 0.704, RF shows an accuracy of 0.709, GBM shows 0.705 and SVM shows an accuracy of 0.699. After comparison with various models, RF gives better accuracy. RF is a non-parametric model its maximum tree depth and number of features chosen randomly at each tree node are optimised.

3.2 Dense Net

DenseNet is one of the CNN-based deep learning models. As the name says Densely Connected Convolution Network has an architecture of layers where each layer is densely connected to every other layer. DenseNet concatenates the output feature maps of the layer with the incoming feature maps.

$$X_1 = H_1([x_1, x_2, x_3, x_4, \ldots, x_{1-1}])) \quad 1$$

The feature map's size is not even throughout the model so, the equation (1) is not valid for different sizes of feature maps hence to overcome this issue, DenseNet is divided into Dense Blocks. These are the blocks in which the number of filters is different but the dimensions of the feature maps are the same within the block. The layers that lie in between these dense blocks are referred to as transition layers. The transition layers do the convolution and pooling that performs the down-sampling by applying batch- normalisation. As each layer produces K-feature maps which get concatenated to the earlier feature maps hence, for later layers in the network the number of inputs is quite high. This results in greater computational requirements and makes it more efficient hence using bottleneck layers. DenseNet has different versions like DenseNet121, DenseNet161, DenseNet201, etc. The suffix denotes the number of layers in the neural network. DenseNet161 is computed where 5 indicates the total number of convolution and pooling layers, there are 3 transition layers which get the input from each dense block which contains 6,12 and 36 layers respectively and there is 1 classification layer which contains 24 layers and within each dense block there are 2 types of convolutions that is 1x1 and 3x3. The advantage of using DenseNet is that the error signal is effectively transmitted to previous layers in a more straight-off manner. This is a sort of implied deep oversight/supervision as previous layers can get immediate oversight from the last classification layer. Each layer is fed by all of its previous layers as inputs that help in providing richer learning patterns and trends due to the involvement of more varied features. This extent of involving discrete complexity levels of feature maps pushes the classification based on DenseNet to smooth decision boundaries.

DenseNet has different versions like DenseNet121, DenseNet161, DenseNet201, etc. The suffix denotes the number of layers in the neural network. The suffix 161 is computed as follows:

DenseNet161:

$$5+(6+12+36+24)\ *2 = 161$$

Which comprises 5- Convolution and Pooling Layer, 3-Transition Layer of 6, 12, 36,1- Classification Layer (24), 2- DenseBlock with 1x1 and 3x3 conv filters

In ResNet, the output of layer n is given as:

$$x[n] = f(w * x[n-1] + x[n-2])---------- \quad (2)$$

In DesneNet the output of layer n is given as:

$$x[n] = f(w * H(x[n-1], x[n-2], \ldots x[1]))\text{--------} \quad (3)$$

The number of filters in DenseBock changes as the dimension of the channel increases. The growth rate is given by (g) which helps in generalising the i-th layer.

$$^{[1]} = (g^{[0]} + g(1-i))\text{----------} \quad (4)$$

4.0 Methodology

4.1 Preprocessing of Dataset

In the back end, the dataset containing a series ofimages is captured continuously into frames from a football match video. The image dataset has been pre-classified into major moves corresponding to the football game i.e., passing, tackling, saving, shooting, dribbling etc.

The pre-classified image dataset is super-resolution using a pre-trained EDSR model to improve the quality of the image by 4x resolution upscaling in order to obtain better results.

4.2 DenseNet161

The super-resolution image dataset is divided into train and validation in an 80:20 ratio. A pre-trained DenseNet161 model that uses MxNet as the backbone is implemented over the dataset for 30 epochs and batch size 4. A SGD is chosen as the optimiser with 0.01 as its learning rate.

Once the model is trained for the given input dataset, perform a model evaluation that indicates the measure of accuracy of the model. If the model has an underfitting or overfitting the model is trained all over again by updatingthe hyperparameters. If the model does not have any kind of underfitting or overfitting the model is used for the inference part.

4.3 Inference and Confusion Matrix

The image uploaded by the user is passed to theinference. The inference is drawn from thetrained model. In this step, the upcoming move'sprediction with a confidence score that depictsthe accuracy of prediction is obtained. A confusion matrix is implemented over a new set of images that provides direct comparisons of values like True and False positives and negatives with which the prominent predictive analysis like accuracy can be visualised to evaluate the modelperformance.

The performance of the model is compared with ResNet152 and the values of various hyper-parameters like training accuracy and loss, validation accuracy and loss, best validation accuracy, etc., and plotted graphs for the obtained results to conclude which is the best model and how fit the model is for the given dataset.

The proposed methodology uses DenseNet161 which uses MxNet as its backbone to predict the upcoming move of the player. The system is trained by a pre-classified dataset that is divided into major moves of the football game by taking the player's body movement and attitude into consideration. This ahead-of-time forecast helps the mentors/coaches in a superior game strategy planning process.

The workflow of the proposed model shown in Figure 1 starts with the score IT website which is designed for football players' movement prediction, it allows the user to select a new image to upload to obtain the next move. Firstly, the dataset contains a series of images captured continuously into frames from the football match game video that is being collected. The image dataset has been pre-classified into major moves corresponding to the football game i.e., passing, tackling, saving, shooting, dribbling etc. The pre-classified image dataset is super-resolution using a pre-trained EDSR model to improve the quality of the image by 4x resolution upscaling to obtain better results.

Then the super-resoluted dataset is split into 80% train and 20% validation datasets. The images are trained upon a pre-trained DenseNet161 model which uses the SGD as an optimiser with 0.01 as the learning rate value. Once the model is trained for the given input dataset, a model evaluation that indicates the measure of the accuracy of the model is performed. If the model has an underfitting or overfitting the model is trained all over again by updating the hyperparameters. If the model does not have any kind of underfitting or overfitting the model is used for the inference part. The image uploaded by the user is passed to the inference code. In this step, the upcoming move's prediction with a confidence score that depicts the accuracy of prediction is obtained.

The model evaluation is presented by comparison model in which the same dataset is trained by DenseNet161 and ResNet152 the performance metrics are compared with the Confusion Matrix in which the truth value and predicted value are compared and accuracy can be estimated for a new set of images through which we can infer the model performance.

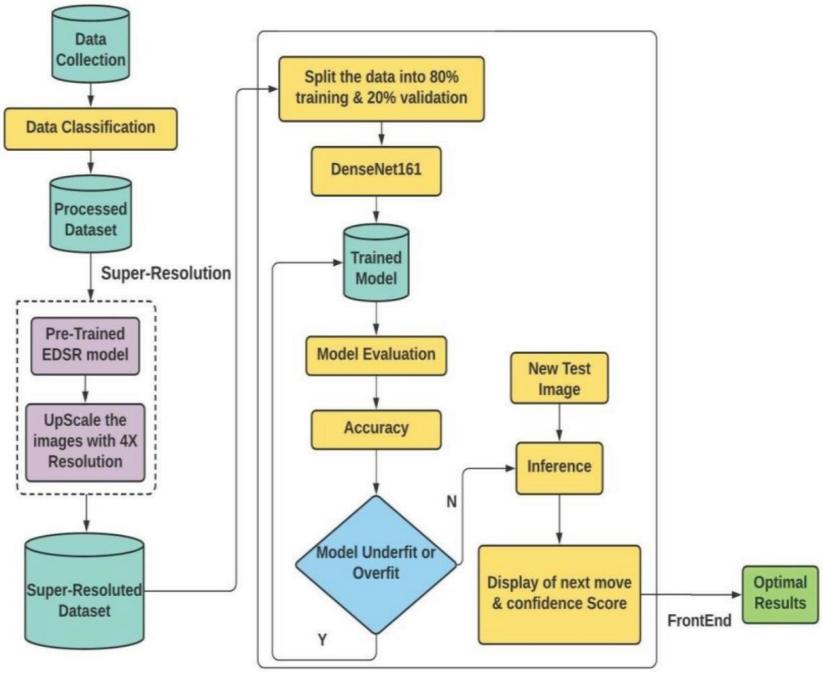


Figure 1. Proposed flow of work.

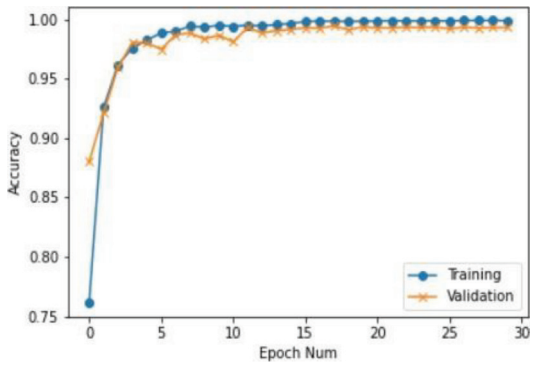


Figure 2. Train-validation accuracy.

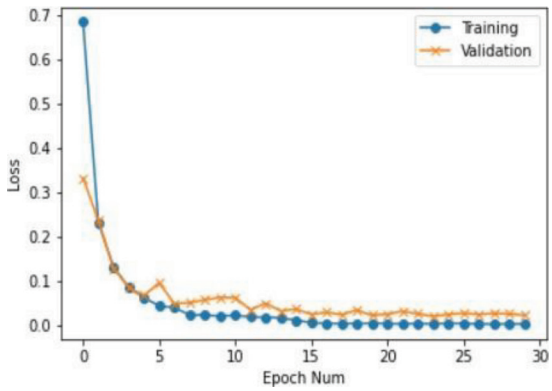


Figure 3. Train-validation loss.

5.0 Results and Discussion

The dataset is unbalanced in such an application. Creating a labeled dataset is the major challenge unsupervised learning is one of the widely used areas in sports. Strategy analysis is done with more accuracy than supervised learning. It takes the suitable attribute as its input from the dataset and produces the accurate output by identifying patterns and strategies in the player's movement[17].

Figure 2 shows the graph comparing the training and validation accuracy of the DenseNet161 model, where X and Y-axes denote the epoch number and accuracy respectively.

Table 1. Confusion matrix

Player Movement	Precision	Recall	F-Measure
Dribbling	1.00	0.95	0.97
Passing	0.91	1.00	0.95
Tackling	1.00	0.95	0.97
Shooting	1.00	0.90	0.95
Saving	0.91	1.00	0.95

Figure 3 shows the graph comparing the training and validation loss of the DenseNet161 model, where X and Y-axes denote epoch number and Loss respectively.

Table 1 displays the Confusion Matrix that denotes the performance of the classification model over a set of test data.

- **ResNet152**

The super-resolved dataset is now divided into train and validation datasets. The ResNet152 models that use MxNet as their backbone are implemented to do a comparative study to identify the best model.

- **Performance Analysis (DenseNet161 vs ResNet152)**

A comparative study of the two trained models (DenseNet161, ResNet152) is performed. Performance metrics such as training accuracy and loss, validation accuracy and loss, training time and best validation accuracy are compared, and the results are obtained in the form of a graph.

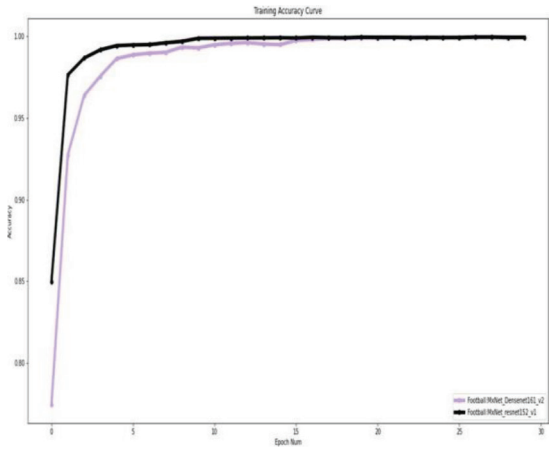


Figure 4. Training accuracy between DenseNet161 vs. ResNet152.

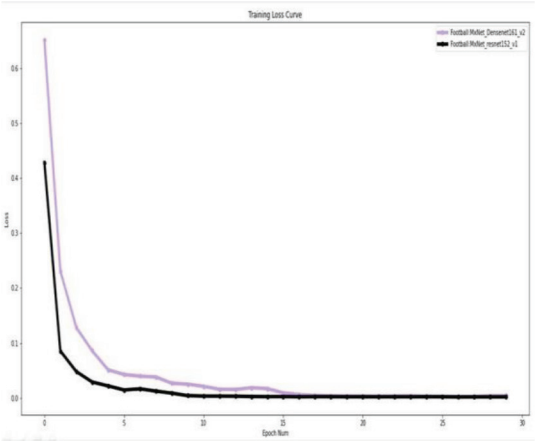


Figure 5. Training loss between DenseNet161 vs. ResNet152.

In Figure 4 a graph comparing the training accuracy of DenseNet161 and ResNet152 is shown, where X and Y-axes denote the epoch number and accuracy respectively. The graph displays that initially, the training accuracy of DenseNet161 is quite low when compared to ResNet152 but gradually both models gained a stabilised accuracy over a greater number of epochs.

In Figure 5 a graph comparing the training loss of DenseNet161 and ResNet152 is shown, where X and Y-axes denote the epoch number and loss respectively. The graph displays that the training loss of DenseNet161 is quite high initially when compared to ResNet152 but gradually both of the models gained an equal loss over more epochs.

In Figure 6 a graph comparing the validation accuracy of DenseNet161 and ResNet152 is shown, where X and Y-axes denote the epoch number and accuracy respectively. The

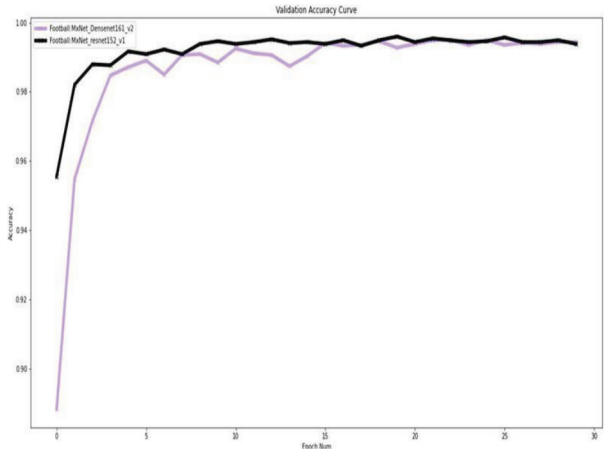


Figure 6. Validation accuracy between DenseNet161 vs ResNet152.

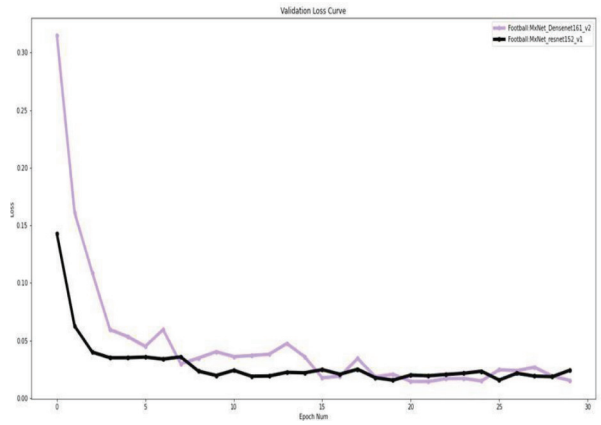


Figure 7. Validation loss between.

graph displays that the accuracy of DenseNet161 is quite low initially when compared to ResNet152 but gradually both models gained an equal loss over a greater number of epochs.

In Figure 7, a graph comparing the validation loss of DenseNet161 and ResNet152 is shown where X and Y-axes denote the epoch number and loss respectively. The graph displays that the loss of DenseNet161 is quite high initially when compared to ResNet152 but gradually the loss of DenseNet161 is low when compared to ResNet152 at the end of the 30th epoch which denotes DenseNet161 is the best fit for the dataset when compared to ResNet152. The loss was due to the overcoming of the vanishing gradient limitation of ResNet152 by DenseNet161 model.

Table 2 performance analysis of the proposed model with super-resolution. The model performed well with 30 epochs and the inference shows accurate results with 99% accuracy in the classification of the player's movement.

Table 3 shows the comparative study with different optimisers. The proposed model showed optimal results with the SGD optimiser rather than the Adam optimiser.

Table 4, represents the values of various parameters like train accuracy and loss, validation accuracy and loss and best validation accuracy that are obtained at the 15th, 20th and 30th epochs of two different trained models for a comparative analysis i.e., DenseNet161 and ResNet152. Train accuracy is the same for both the models but validation accuracy is good with the DenseNet161 model and loss is comparatively less with DenseNet161. The results of DenseNet and ResNet are compared using precision, recall, f1-score and support.

Table 2. Performance analysis

Model Parameters	With Super Resolution		
Epochs	15	20	30
Train Accuracy	0.997	0.999	0.999
Validation Accuracy	0.9951	0.9491	0.9957
Train Loss	0.013	0.005	0.005
Validation Loss	0.019	0.017	0.017
Best Train Accuracy	0.99		
Inference	Accurate		

Table 5. Accuracy measure of ResNet152 and DenseNet161

Optimizer	Model	Precision	Recall	f- Score	Support
Adam	Res Net 152	0.70	0.93	0.80	196
SGD		0.70	0.96	0.81	196
RMS Prop		0.57	0.89	0.69	196
Adam	Dense Net 161	0.87	0.95	0.91	183
SGD		0.92	0.92	0.92	183
RMS Prop		0.88	0.96	0.92	183

Table 3. Performance analysis with different optimisers

Optimizer	Epochs	Train Loss	Train Accuracy	Validation Loss	Validation Accuracy	Inference
SGD	15	0.013	0.997	0.019	0.99517	Accurate
	20	0.005	0.999	0.017	0.9491	
	30	0.005	0.999	0.017	0.99571	
ADAM	15	0.047	0.985	0.064	0.982	Ambiguous
	20	0.029	0.991	0.044	0.996	
	30	0.020	0.994	0.037	0.990	

Table 4. Performance analysis of two different models

Model	Epochs	Train Loss	Train Accuracy	Validation Loss	Validation Accuracy
Dense Net161	15	0.017	0.995	0.036	0.990
	20	0.002	0.999	0.021	0.993
	30	0.002	0.999	0.015	0.994
ResNet152	15	0.002	0.999	0.022	0.994
	20	0.004	0.999	0.016	0.996
	30	0.004	0.999	0.024	0.993



Figure 8. Predicted move – dribbling.

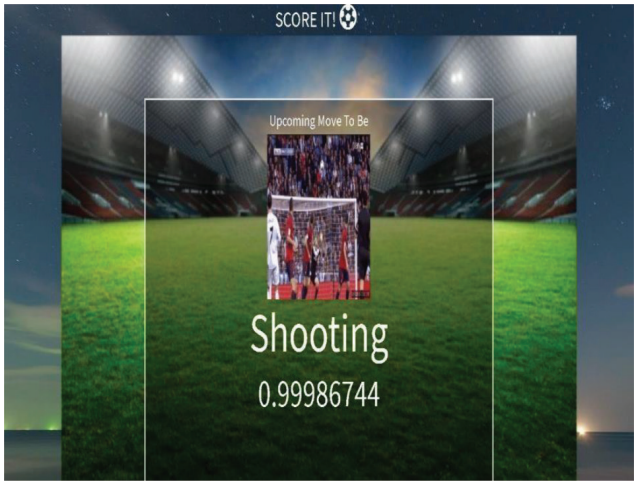


Figure 9. Predicting move: Shooting.

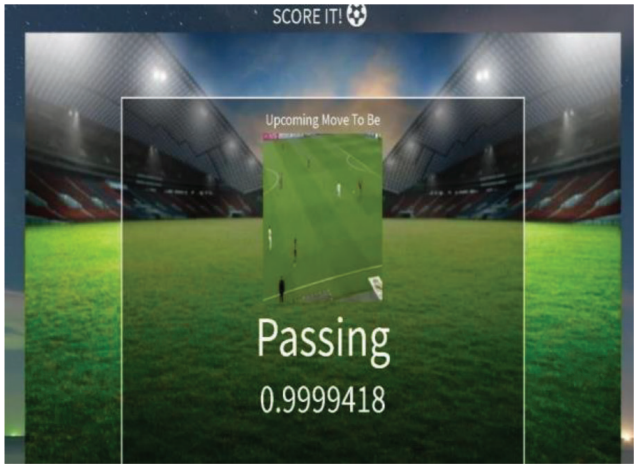


Figure 10. Predicted move –passing.

Table 5 shows the comparative study of both models by varying various optimisers.

Figures 8, 9 and 10 show the predicted results for new images when input to the proposed model. The predicted move for the input image is dribbling, shooting and passing with good accuracy. Hence the model is good at predicting the next movement of players which helps to plan the game strategy for the team and coaches. It is observed that the time taken for training ResNet152 is 23000 sec less when compared to DenseNet161 which is taking is 27000 sec.

6.0 Conclusion and Future Scope

The proposed model uses a Deep Learning framework with integrated support of Computer Vision technology that has helped in predicting the next move of the football player. The model plays an important role in the game strategy planning process for teams and coaches. This would help to increase the success rate of a team through their powerful gameplay. Using DL technology one can even propose various other forecasts in other sports like basketball, cricket, baseball etc. The prediction can be more specific by including an automated player-tracking and ball-tracking mechanism. Sports as an aid of entertainment strengthens learning strategy for beginners. It helps the managing staff to reveal critical determinants of team performance and to design better game strategies.

Future work can be done by designing a system that predicts the upcoming move of a player byconsidering the overall group of players. Further exploration can be done by enhancing the model and providing better forecasts that impact the team's success in sports. Similarly, these CNN-based models and computer vision techniques can be used in mining industries to forecast air-blast overpressure in mines with open pits and to distinguish the source area of microseismic occasions based on recorded ground tremors, therefore preventing min catastrophe.

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