DETECTION OF CRICKET ACTIVITY USING DEEP LEARNING

A PROJECT REPORT

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BONA FIDE CERTIFICATE

Certified that this project report titled PREDICTIONS ON CRICKET is the bona fide work of KEERTHNA A J and PRIYA J who carried out project work under my supervision. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Cricket is the most enjoyed game in Asian Subcontinent. Test match, One Day International and T20 are three internationally recognized formats of cricket matches. Cricket is a bat-and-ball game played on a cricket field between two teams of eleven players each. Before a match begins, the team captains toss a coin to decide which team will bat first and so take the first batting. Innings is the term used for each phase of play in the match. In each innings, one team bats, attempting to score runs, while the other team bowls and fields the ball, attempting to restrict the scoring and dismiss the batters. When the first innings ends, the teams change roles; there can be two to four innings depending upon the type of match. Cricket is a sport that contains lots of statistical data like batting and bowling record of the team, an individual player's record, a scoreboard of different matches played, fall of wickets, run rate during the match and many others. Before starting a cricket match, opposite team does some analysis based on this statistical data, to find the weakness of the opposite team.It is a challenging task due to the diversification of different cricket stances and emblems in batting, bowling and umpiring, variations of wickets and the complexity in cricket actions which is focused. The aim is to detect the diverse incidents which come to pass throughout a cricket match with the help of CNN. It includes different cricket shots played by the cricketers.These includes drive shot,pull shot,sweep shot,square cut,wide,umpire out and umpire six.It uses One Cycle Policy to make a robust and time efficient model.For comparison and to provide a better understanding, four other customized models namely ResNet34, ResNet50, ResNet101, VGG16 with Batch Normalization and AlexNet are studied in this project.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

API	Application Programming Interface
CNN	Convolutional Neural Network
FLOPS	Floating Point Operations Per Second
IPL	Indian Premier League
ODI	One Day International
VGG	Visual Geometry Group

CHAPTER 1

INTRODUCTION

Cricket is referred as Game of Uncertainty and there is no any precise forecast that a specific team would win in any given conditions.Cricket is the second most popular sports in the world with billions of fans across India, UK, Pakistan, Africa, Australia, etc. It is an outdoor game played on a cricket field at 22-yard rectangular long pitch, between two teams consisting each of 11 players. It is played in three formats namely Test, One Day International and Twenty Over International.

Unlike other sports, cricket stadium's size and shape is not fixed except the dimensions of the pitch and inner circle which are 22 yards and 30 yards respectively. The cricket rules do not mention the size and the shape of the field of the stadium. Pitch and outfield variations can have a substantiate effect on batting and bowling. The bounce, seam movement and spin of the ball depends on the nature of the pitch. The game is also affected by the atmospheric conditions such as altitude and weather. A unique set of playing conditions are created due to these physical differences at each venue. Depending on these set of variations a particular venue may be a batsman friendly or a bowler friendly.

In this project, a method has been proposed in which the activities of players in the cricket match are detected using CNN [1]. Activities include drive shot,pull shot,sweep shot,square cut ,umpire out ,umpire six and wide.

The domain of this project is deep learning [2]. Deep learning is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for use in decision making systems.

Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised data that is unstructured or unlabeled. It is also known as deep neural learning or deep neural network. Deep Learning has proved to be a very powerful tool because of its ability to handle large amounts of data. The interest to use hidden layers has surpassed traditional techniques, especially in pattern recognition. One of the most popular deep neural networks is CNN. CNN is a type of artificial neural network used in deep learning to evaluate visual information. These networks can handle a wide range of tasks involving images, sounds, texts, videos, and other media. ResNet34, ResNet101, VGG16 with Batch Normalization and AlexNet are used in this project. It uses One Cycle Policy to make a robust and time efficient model

ResNet34 : ResNet34 [3] is a 34 layer convolutional neural network that can be utilized as a state-of-the-art image classification model. It is an image classification model pre-trained on ImageNet dataset. For ResNet34, we have four residual blocks with config — 3,4,6,3.

ResNet50 : ResNet50 [4] is a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer.Resnet50 is used to denote the variant that can work with 50 neural network layers.The model consists of 5 stages each with a convolution and Identity block. Each convolution block has 3 convolution layers and each identity block also has 3 convolution layers. It has over 23 million trainable parameters.

ResNet101 : ResNet-101 [5] is a convolutional neural network that is 101 layers deep. It can be loaded with a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

VGG16 : VGG16 [6] is a type of CNN that is considered to be one of the best computer vision models to date. The model has evaluated the networks and increased the depth using an architecture with very small (3×3) convolution filters.VGG16 is object detection and classification algorithm with 92.7 percent accuracy. It is one of the popular algorithms for image classification and is easy to use with transfer learning.

Alexnet : AlexNet [7] is the name of a convolutional neural network which has had a large impact on the field of machine learning, specifically in the application of deep learning to machine vision.AlexNet allows for multi-GPU training by putting half of the model's neurons on one GPU and the other half on another GPU. Not only does this mean that a bigger model can be trained, but it also cuts down on the training time.

1.1 OBJECTIVE

Objective of this project is to detect the activities of cricket such as drive shot, pull shot, sweep shot, square cut ,umpire out, umpire six and wide using deep learning with the help of CNN by analysing various data. For comparison and to provide a better understanding, four other customized models namely ResNet34, ResNet50, ResNet101, VGG16 and AlexNet are used in this project.

1.2 CHALLENGES

The challenges for the proposed work are listed here. Most of the data available are raw data which are needed to be processed before using for training and testing. Datasets had many missing values which required handling of the records.It is a challenging task due to the diversification of different cricket stances and emblems in batting, bowling and umpiring, variations of wickets and the complexity in cricket actions which we focus to research in our work. Developing a real time system to detect these signs, batting actions, incidents from images is a great challenge.

1.3 APPLICATIONS OF DEEP LEARNING

Deep learning is a part of machine learning field consisting of learning representations of data.It is exceptionally effective at learning patterns.It utilizes learning algorithms that derive meaning out of data by using a hierarchy of multiple layers that mimic the neural networks of our brain.If it is provided with the system tons of information,it begins to understand it and respond in useful ways. Deep Learning is the force that is bringing autonomous driving to life.Deep learning has introduced new ways to look at technologies.Deep Learning are being used in daily life even without knowing it such as Google Maps, Google assistant, Alexa, etc.
Some most trending real-world applications of Deep Learning:

Self driving cars :The major concern for autonomous car developers is handling unprecedented scenarios. Data from cameras, sensors, geo mapping is helping create succinct and sophisticated models to navigate through traffic, identify paths, signage, pedestrian-only routes, and real-time elements like traffic volume and road blockages.Deep learning is commonly used to do this.
Convolutional neural networks (CNN) are used to model spatial information, such as images. CNNs are very good at extracting features from images, and they're often seen as universal non-linear function approximators . CNNs can capture different patterns as the depth of the network increases. For example, the layers at the beginning of the network will capture edges, while the deep layers will capture more complex features like the shape of the objects like leaves in trees, or tires on a vehicle. This is the reason why CNNs are the main algorithm in self-driving cars.The car has a 360-degree view of its environment

that enables it to perceive and capture all the information and process it. Once fed into the deep learning algorithm, it can come up with all the possible moves that other road users might make. It's like a game where the player has a finite number of moves and tries to find the best move to defeat the opponent.

News aggregation : Deep learning is being used extensively in news aggregation, which is assisting efforts to personalise news for individual readers. While this may not seem new, newer levels of sophistication to define reader personas are being met to filter out news as per geographical, social, economical parameters along with the individual preferences of a reader.These days the government takes a lot of effort especially in controlling the spread of fake news and origin of it. Also during poll surveys like who would win elections in terms of popularity, which candidate been shared by most people in social media etc and analysis of tweets made by country people using all these variables we can predict the outcomes in deep learning, but also there are some limitations to it, we don't know the data authenticity whether its genuine or fake. etc or whether the necessary information been spread by bots.

Healthcare : Deep learning is the swift-augmenting trend in healthcare. Wearable sensors and devices that use patient data in order to provide real-time data about patient conditions such as overall health condition, blood sugar level, blood pressure, heartbeat counts, and various other measurements use deep learning.Deep learning is assisting medical professionals and researchers to discover the hidden opportunities in data and to serve the healthcare industry better. Deep learning in healthcare provides doctors the analysis of any disease accurately and helps them treat them better, thus resulting in better medical decisions.The technology analyzes the patient's medical history and provides the best treatment for them. Moreover, this technology is gaining insights from patient symptoms and tests. Deep learning in healthcare can provide doctors and patients with astonishing applications, which will help doctors to make better medical treatments.

Fraud news detection : Fraud news detection is an important asset in today's world where the internet has become the primary source of all genuine and fake information. It becomes extremely hard to distinguish fake news as bots replicate it across channels automatically.Deep Learning helps develop classifiers that can detect fake or biased news and remove it from your feed and warn you of possible privacy breaches.Too often, especially on the social media feeds, we come across lots of fake news that is highly misleading and unethical for those who publish them. Although this is not new, deep learning extensions can help trigger true and false information across the internet. Deep learning's broad use can even help eliminate all the harmful and fraudulent news out the online premises entirely. Also, fake news travels fast. But with deep learning, we can eliminate that aspect.Due to this advanced technology people easily trust banks and online transactions, and believe in digital security.Fraud prevention and detection are done dependent on recognizing designs in client transactions and credit scores, distinguishing bizarre conduct and anomalies.Therefore, classification and various regression techniques under machine learning methods and neural networks are used for fraud detection.

Image – Language Translations : A fascination application of Deep Learning includes the Image – Language translations. With the Google Translate app, it is now possible to automatically translate photographic images with text into a real-time language of your choice. This is an extremely useful application considering that languages will gradually stop being a barrier, allowing universal human communication.Convolutional neural networks are useful in identification of images that have visible letters. Once identified, they can be turned into text, translated and recreated with an image using the translated text. This process is called Instant visual translation. This application involves automatic translations into another language with a set given words, phrase or sentence in one language. While Automatic machine translation has been around for a long time, but deep learning is achieving top results in two specific areas namely automatic translation of text and automatic translation of images. Text translations are usually performed without any preprocessing of the sequence. This allows the algorithm to learn the dependencies between words to map it into a new language. These tasks are generally performed by stacked networks of large recurrent neural networks.

Virtual assistants : The most popular application of deep learning is virtual assistants ranging from Alexa to Siri to Google Assistant . Virtual assistants use deep learning to know more about their subjects ranging from your dine-out preferences to your most visited spots or your favorite songs . These virtual assistances do have much more than just replying to your answers, and they use deep learning algorithms not to understand your language merely but also to perform such mind-blowing things. Things like setting the alarm, playing music, scheduling, and more, virtual Assistant caters to them all. Virtual assistants are actually available at your beck-and-call as they can do everything from getting things done to auto-reacting to your particular calls to planning assignments among you and your colleagues.Another power virtual assistants are invested in is interpreting your speech to message, make notes for you, and book arrangements.With deep learning applications like text generation and record synopses, virtual assistants can help you in making or sending proper email duplicates also.

Deep Learning has brought about a positive change in most of the fields. It can also be applied in sports like cricket.Deep learning aids in the recognition of patterns in cricket. It is always important to select the correct variables so that the prediction is accurate.

1.4 MOTIVATION

The primary motivation behind this project is increasing popularity of cricket matches. This project will be interesting for biggest cricket fans and also the motivation for choosing this work is that this can be a major step in further developing an automatic commentary system which would be a huge contribution to the field of sports.

1.5 ORGANIZATION OF THE REPORT

The rest of the report is organized as follows:

Chapter 2 discusses about the Literature survey which summarizes the related works that had been published related to the current system. It also describes how this system is enhanced to overcome the limitations of the existing system.

Chapter 3 discusses about the System architecture which describes the overall work flow, with detailed explanation of the modules in the architecture diagram.

Chapter 4 deals with the implementation of the work which explains about the details of how this system has been implemented with the algorithms which discusses the procedure and workflow of implementation.

Chapter 5 emphasizes the results and performances of this system with screenshots of the output.

The reference papers and the websites which are referred for this project is given at the end of the report

CHAPTER 2

LITERATURE SURVEY

For our cricket data analysis,a quite number of research papers related to our task had been studied, which is shortly discussed here.

Using Convolutional Neural Network and transfer learning: Miftaul Mannan et al [5] approached an image classification which is based on cricketing activities with the help of Convolutional Neural Network, ResNet50, as ResNet models are better than any other convolutional neural network models for image classification. Fundamentally the aim is to detect the diverse incidents which come to pass throughout a cricket match. It includes different cricket shots played by the cricketers, several symbols which are betokened by the umpires. This scheme has compelled us to develop a distinct absolute dataset Cricket Image Classification (CIC), consisting of various cricketing incidents. Due to the scarcity of ready images, this paper utilizes transfer learning. It had gone for a process called transfer learning where the model is pre-trained on the ImageNet dataset. It used an optimizer, Adaptive Moment Estimation as they have implemented varying learning rates in combination with One Cycle Policy for quick training.This paper approaches a custom ResNet50 model together with the utilization of One Cycle Policy to make a robust and time efficient model . For comparison and to provide a better understanding , four other customized models namely ResNet34, ResNet101, VGG16 with Batch Normalization and AlexNet are introduced and studied in this paper . In this paper,own set of dataset has been established which is called as Cricket Image Classification (CIC) that consists of 9 different cricket activities including batting action, umpiring signal and incidents.Limitations of this paper includes

- The frames on the videos will contain full pitch where more than one player is included and the model finds it difficult to pick the active and eventful player from the videos.
- This model can identify only few kinds of incidents from the images which lack many more incidents occurring in a cricket match.
- Dataset images need to be given accurately excluding all other factors in the frame in order to get accurate prediction results.

Using motion vector: D Karmaker et al [4] suggested the following approach. A spatio-temporal maximum average correlation height filter is used to recognize action. The filter can capture intra-class variability synthesizing a single action MACH for a class. Cricket shots also related to human pose and action. Here, traditional MACH filter is generalized to video (3D spatiotemporal volume), and vector valued data.They have made the MACH of video of specific shots. This can be considered as training set. They made the training set from 6 videos for each shots. MACH actually make the cluster of the videos. Now a tested video of shot is correlated with the MACH, it will get the specific frames that matched with shot. In use 6 videos to learn every shots and checked it with another video of that correspondent shot. If the match is occurred it will make another video of the specific frames that get match with the test video. When the match of the test action is matched the action is a cricket shot that is detected. The MACH 3D is actually developed by Rodriguez for detect specific action. Using this approach,cricket shot action is detected.The input video is correlated with the volume. In final result of detected video we can see that only 7 frames that are matched for the actual cricket action. But testing video has 31 frames. We only select those frames that have matched that particular action and make another video that depict the matched frames only. After recognition of an event i.e. any particular cricket shot, our approach is to detect shot using several range of angle of optical flow vectors of each pixel.There are several approach for evaluating optical flow using a modified approach of Lucas Kanade. Then motion vector for each of the pixel of each of the frame is obtained.The approach we have figured out gives the summation of vectors corresponds to 4 shots. Right now with this approach, 8 shots can be detected.They have tested on 4 shots and the results of 3 shots are visualized .Limitations of this paper includes

- Using single camera it is hard to make best precision of flow of bat and actual 3D model of angle.
- This model has focussed only on batting player and not on other factors of cricket match.
- It include motion blur in a reflective surface, deformation blur, no true 3D motion blur effects.

Using image processing: Ashok Kumar et al [1] focussed on the analysis of broadcast video for cricket. An important task here is to analyze the type of scene being shown - e.g. if it is a crowd view, or if it is towards the end of the ball, perhaps there is time to insert a small commercial break; however, if the play is in the pitch view, chances are that the ball may be about to be bowled, in which case a break would be very unwise. Another aspect is to detect the type of stroke played by the batsman - is it towards the on-side or off? Here they classified the cricket strokes played by a batsman into four different directions.Shot boundary detection is the first step used for segmentation and classification of a video data.They created their own dataset for training and testing. For this they chose an 8 over cricket match video played between Australia and England (25 fps). Training and testing were done using K-fold cross validation method with K=3. Approximately 29000 frames were manually analyzed for training purposes and about 14000 frames were used for testing. In this approach they represented each frame as a feature vector.To generate feature vector corresponding to a frame we represent each frame as a YUV image histogram which stores the total number of pixels in each bin, feature vector generation and classification is used.They quantized the UV plane of the color space into 40x40 bins and using these histograms, compute squared difference with histograms of previous 30 frames. Training and testing were done using K-fold cross validation method.For cut and fade classification in testing data, K NN algorithm has been used. This project has few limitations including

- Accuracy rate was not much high.
- Dataset was not from diverse matches.
- If these datasets are handled properly,prediction would have been more accurate.

Using 2D and 3D convolution network: Muhammad Zeeshan Khan et al [3] had proposed deep CNN based Data-driven Recognition of Cricket Batting Shots.They evaluated performance for selection of video frames. Details of each experiment has been presented in subsequent sections. The input to their model is in a form of video in which they convert the each frame into the specific size depend upon our architecture requirement then we map output for the eight possible classes, one for the each possible outcome.Their dataset is the screenshots of cricket activity obtained from youtube videos. In order to make the back propagation for the updation of the weights, stochastic gradient descent had been used.While dealing with video inputs, frame level processing takes critical part in determining the overall framework computational complexity and performance. Processing each frame for high definition videos with high frame rate requires huge memory. Therefore, they have performed experiments with all frames of video as well as for selected frames. For all frames architecture, each frame is processed through famous AlexNet and scores for each batting shot category is averaged across all frames to get the single score vector for a given video. In other setup, only five frames per video have been passed through the network and results are computed.In 2D convolution neural networks,the 2D kernels are performing the convolution on images to extract the features maps. Each convolution layer have specific numbers of filters or kernel and produce the specific numbers of feature maps that are further used by the next convolution layer. And the finally the linear layers get features from convolution layers and predict the the scores of different classes. Since the task requires the understanding of both visual and motion change over time, VGG16Net has been employed.A 3D convolutional neural network is similar to 2D convolutional network but it also takes depth factor in account and performs convolution on the contiguous frames in spatial and temporal dimensions of video to extract representations. These features are useful for analyzing the motion of objects in videos as they capture spatial and temporal aspects simultaneously. The 3D convolution is done by convolving a 3D kernel on contiguous frames of video and generating the specific number of 3D feature maps depending on the number of 3D filters or kernel of this layer, and then these 3D feature maps are passed to next 3D convolution layer. The following are some of the project's limitations:

- The dataset used in these works are limited.
- The accuracy rate is not significantly greater.
- Dataset has images that only considers the clips with frontal camera view.

2.1 EXISTING WORK

Miftaul Mannan et al utilised an image classification that is based on cricketing activities with the help of Convolutional Neural Network,ResNet50.

They had also used transfer learning on dataset. D Karmaker et al suggested using motion vector approach.A spatio-temporal maximum average correlation height filter is used to recognize action,here. Ashok Kumar et al focussed on the analysis of broadcast video for cricket using image processing technique.K-fold cross validation method has been used here for training and testing.Deep CNN based Data-driven Recognition of Cricket Batting Shots was given by Muhammad Zeeshan Khan et al. They assessed performance in terms of video frame selection.

Limitations of existing works includes predominantly not higher accuracy rate of prediction,dataset with only specific position of views,difficulty in training the model,fewer records in the dataset,dataset with just certain view positions,

2.2 PROPOSED WORK

The proposed work is to use deep learning and CNN to detect cricket behaviours such as drive shot, pull shot, sweep shot, square cut, umpire out, umpire six, and wide utilising various data. Four customised models, ResNet34, ResNet50, ResNet101, VGG16, and AlexNet, are used in this project for comparison and better understanding.

In this chapter, Literature survey is discussed in detail. And also discussed about the existing work of the project and the limitations of the existing work. In the next chapter system architecture and the function modules will be elucidated in detail

CHAPTER 3

SYSTEM ARCHITECTURE

This section deals with the general architecture of proposed model.

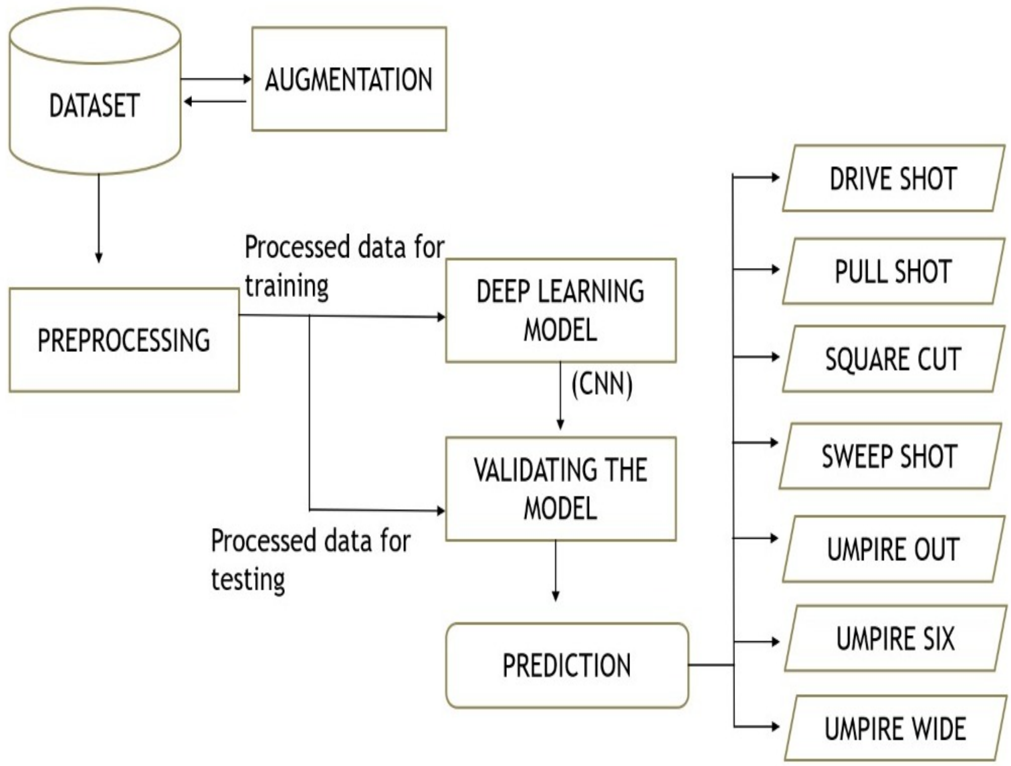

Figure 3.1: Architecture of proposed work

Figure 3.1 depicts the architecture representation the proposed work.The dataset is created by taking screenshots from videos and it is augmented.Then they are preprocessed,and splitted for training and testing purposes.CNN models are used for this process.After this the specific cricket activity is detected.

3.1 FUNCTION MODULES

3.1.1 Dataset

Dataset is manufactured from the scratch for the project. This dataset comprises a variety of cricket match occurrences. Various types of batting stroke, bowling, wicket were consolidated. The dataset consists of 3,233 images of different cricket activities.Figure 3.2 represents few of those samples from the dataset that has been created.Each class contains images taken from varying angles to help train the model for general case. Since the dataset is small, we ended up using most of it for training and validation because deep neural networks need a lot of data to converge. For this project an imagenet style dataset is chosen. Imagenet dataset contains 3 folders (train, valid and test) and the train and valid folder contains subfolders equal to the number of classes. Each class folder contains numerous images of the same class. Test folder doesn't contain any classes since it is considered to be unlabeled. It only contains images to be tested. Several samples from the dataset is shown below.

3.1.2 Preprocessing

Preprocessing data is a common first step in the deep learning workflow to prepare raw data in a format that the network can accept. It is done to make the data suitable for our model. The dataset images and labels were needed to be processed before they can be used for training the model. As our dataset contains images with different sizes, resizing is needed to both work with our model and bring them to be of the same dimensions. So all the images are

Figure 3.2: Samples from dataset

resized to the size 224X224. Imagenet stats are used to normalize the data as transfer learning is used on models pre trained with imagenet dataset to reduce and eliminate data redundancy.

3.1.3 Augmentation

Data augmentation is a technique used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. Neural networks need a lot of data to work with in order to give better results. Since the dataset was handcrafted, augmentation is used for increasing the dataset size. The augmentation part is done by initializing the augmentation object for the training set with random flips (horizontal flip, vertical flip), zoom in, zoom out, lighting etc.

3.1.4 Deep learning algorithm- CNN

In deep learning, a convolutional neural network (CNN) is a class of deep neural networks, most commonly applied to analyze visual imagery. CNNs are very effective in reducing the number of parameters without losing on the quality of models. CNN is a deep learning technique that uses artificial neural networks to analyse visual data. Images, audio, texts, movies, and other media can all be handled via these networks. The algorithms utilised in this project include ResNet34, Resnet50, ResNet101, VGG16 with Batch Normalization, and AlexNet. It uses One Cycle Policy to make a robust and time efficient model.

Resnet34 is a state-of-the-art image categorization model with 34 layers of convolutional neural networks. It's a pre-trained picture categorization model on the ImageNet dataset. **ResNet50** is a ResNet variation having 48 convolutional layers, one MaxPool layer, and one Average Pool layer. The term Resnet50 refers to a variation that can work with up to 50 neural network layers. Each level of the model has a convolution and identity block. **ResNet-101** is a 101-layer deep convolutional neural network. It can be preloaded with a network that has been trained on over a million photos from the ImageNet database. **VGG16** is a form of CNN that is widely regarded as one of the most advanced computer vision models available. VGG16 is a 92.7 percent accurate object identification and classification system. **AlexNet** is a convolutional neural network that has had a significant impact on machine learning, particularly in the application of deep learning to machine vision.

3.2 WORKFLOW OF THE MODEL

This project approaches an image classification which is based on cricketing activities with the help of Convolutional Neural Network. The motive is to detect the diverse incidents which come to pass throughout a cricket match. It includes different cricket shots played by the cricketers and several symbols.

This is done using ResNet50, ResNet101, ResNet34, VGG16 and AlexNet. For the project, a new dataset is created. A variety of cricket match occurrences are included in this collection. Before the dataset images could be used to train the model, they needed to be processed as the dataset comprises images of various sizes, scaling is required in order for them to interact with our model and be of the same dimensions. As a result, all of the photos have been scaled to 224X224. Transfer learning is employed on models pre-trained with the imagenet dataset to decrease and eliminate data redundancy, and imagenet stats are used to normalise the data and also augmentation is done for increasing the size of the dataset by initializing the augmentation object for the training set with random flips (horizontal flip, vertical flip), zoom in, zoom out, lighting etc. After binding the train, valid and test dataloader in a data object, an ImageDataBunch was created from imagenet style dataset in path with train, test subfolders. The label map is initialized with 7 classes and then training starts.The training had training loss, validation loss, accuracy and timetable for each step. For all the steps in the training, there were subsequent steps for testing(validation) as well. That's how the model was able to learn from mis-predictions and gradual processing of the images. Variations of photos were provided in the testing dataset. Optimization techniques (One Cycle Policy) were applied not to underfit the data. There are a lot of features in an image and not all of them contribute to training the models, Features from the backgrounds are unnecessary because we only need features from the player. Our main focus is to see what the player or umpire is doing. Since transfer learning is used, the models are already quite good at extracting features. They can detect which features are necessary and use dropout to decrease the number of features. After all these the model will be ready for detecting the cricket activities and the comparative study is done to find the model which produces the higher accuracy rate.

3.3 CNN

A Convolutional Neural Network, or CNN, is a form of artificial neural network used for image/object recognition and classification in Deep Learning. Using a CNN, Deep Learning recognises objects in an image. The architecture of the brain inspired CNNs. Artificial neurons or nodes in CNNs collect inputs, process them, and deliver the result as output, just like a neuron in the brain processes and transmits information throughout the body. As input, the image is used. The image pixels are input to the input layer in the form of arrays. Multiple hidden layers may exist in CNNs, which perform feature extraction from the image by performing calculations. Convolution, pooling, rectified linear units, and fully connected layers are examples of this. The first layer that extracts features from an input image is convolution. The object is classified and identified in the output layer by the fully connected layer.

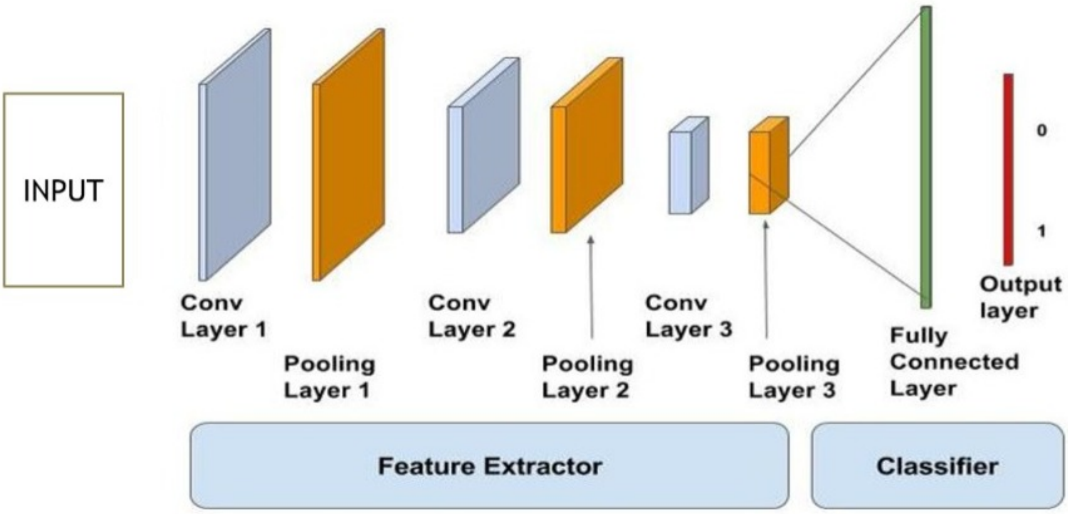

Figure 3.3: CNN Architecture

System Architecture is illustrated in this chapter and all the components were explained explicitly. In the next chapter, Implementation of the project will be talked through and also the outputs of the project will be illustrated.

CHAPTER 4

IMPLEMENTATION

Proposed methodology includes Dataset Collection, Pre-processing of collected dataset, augmenting the available dataset,Feature extraction from raw data, partitioning of samples into training and test samples, training and classification.

4.1 WORKING ENVIRONMENT

The Programming language used in this project is PYTHON 3. Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords often where as other languages use punctuation and it has fewer syntactical constructions than other languages. The project was carried out in Jupyter Notebook [8] with anaconda interpreter.The Jupyter Notebook is an open source web application that can be used to create and share documents that contain live code, equations, visualizations, and text.Its uses include data cleaning and transformation,data visualization, numerical simulation, statistical modeling, machine learning, and much more. Jupyter Notebook is maintained by the people at Project Jupyter.
Anaconda Python is a collection of a number of very useful Python development packages as well as an interpreter. Idle editor is used to build and run Python programs. Idle is included as part of the Anaconda Python installation.

4.2 LIBRARIES AND ALGORITHM

Fastai

Fastai [9] is a deep learning library which provides practitioners with high-level components that can quickly and easily provide state-of-the-art results in standard deep learning domains, and provides researchers with low-level components that can be mixed and matched to build new approaches. It aims to do both things without substantial compromises in ease of use, flexibility, or performance.It is organized around two main design goals: to be approachable and rapidly productive, while also being deeply hackable and configurable

Numpy

NumPy [10] is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays. Using NumPy in Python gives functionality comparable to MATLAB since they are both interpreted and they both allow the user to write fast programs as long as most operations work on arrays or matrices instead of scalars.

Matplotlib

Matplotlib [11] is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK. Pyplot is a Matplotlib module which provides a MATLAB-like interface. Matplotlib is designed to be as usable as MATLAB, with the ability to use Python, and the advantage of being free and open-source.

Python Image Library

Python Imaging Library [12] is a free and open-source additional library for the Python programming language that adds support for opening, manipulating, and saving many different image file formats.It is best suited for image archival and batch processing applications.It incorporates lightweight image processing tools that aids in editing, creating and saving images.

CNN algorithm

In deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters to classify an object. CNN image classifications takes an input image, process it and classify it under certain categories (drive shot, pull shot, sweep shot, square cut, umpire out, umpire six, wide) . Computers sees an input image as array of pixels and it depends on the image resolution.Convolutional neural networks (CNNs) are a type of deep neural network used to analyse visual imagery in deep learning. CNNs are exceptionally good at lowering the number of parameters without sacrificing accuracy.Models of high quality CNN is a deep learning method that employs artificial neural networks.Visual data is analysed using networks. Audio, video, text, and other forms of media can be handled by CNN. In this paper, the algorithms used were ResNet34, ResNet50, ResNet101, VGG16 with Batch Normalization, and AlexNet are just a few examples. It develops a robust and time-efficient model using One Cycle Policy.

ResNet34 :ResNet34 is a state-of-the-art image categorization model with 34 layers of convolutional neural networks . It's a pre-trained picture categorization model on the ImageNet dataset. We have four residual blocks with configuration for ResNet34: 3,4,6,3. It is different from traditional neural networks in the sense that it takes residuals from each layer and uses them in the subsequent connected layers.A classical ResNet-34 model involves 63.5 million parameters, where rectification nonlinearity activation and batch normalization is applied to the back of all convolution layers in the "BasicBlock" block and the softmax function is applied in the final layer.The high-quality features of images can be extracted on ImageNet, due to the good performance of ResNet-34 in image classification.

ResNet50 :ResNet50 is a ResNet variation having 48 Convolution layers, 1 MaxPool layer, and 1 Average Pool layer.It has 3.8 x 10 power to 9 Floating points operations. It is a widely used ResNet model.The Resnet50 variation is one that can work with 50 neural network layers. There are five phases in the model, each with a convolution and identity block. Each convolution block has three levels, and each identity block has three layers as well. It has about 23 million parameters that can be trained.Each of the 2-layer blocks in Resnet34 was replaced with a 3-layer bottleneck block, forming the Resnet 50 architecture. This has much higher accuracy than the 34-layer ResNet model. The 50-layer ResNet achieves a performance of 3.8 FLOPS.ResNet-50 can easily gain accuracy along with the greatly increased of depth.

ResNet-101 : ResNet-101 is a 101-layer deep convolutional neural network. It can be preloaded with a network that has been trained on over a million photos from the ImageNet database. The network has been trained to categorise photos into 1000 different item categories.The network has an image input size of 224-by-224. As a result, the network has learned detailed feature representations for a wide range of objects.

VGG16 :VGG16 is a form of CNN that is widely regarded as one of the most advanced computer vision models available.The model achieves 92.7 percent top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous model submitted. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using Titan Black GPU's. Using an architecture with very small (3 x 3) convolution filters, the model evaluated the networks and increased the depth.The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional layers, where the filters were used with a very small receptive field.Max-pooling is performed over a 2×2 pixel window, with stride 2. Three Fully-Connected layers follow a stack of convolutional layers. The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification non-linearity. VGG16 is a 92.7 percent accurate object identification and classification system. It is a common picture classification technique that is simple to employ with transfer learning.

AlexNet : AlexNet is a convolutional neural network that has had a significant impact on machine learning, particularly in the application of deep learning to machine vision. AlexNet supports multi-GPU training by placing half of the model's neurons on one GPU and the other half on a different GPU. This not only allows for the training of a larger model, but it also reduces the training time.AlexNet was the first convolutional network which used GPU to boost performance.AlexNet architecture consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer.Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU.The pooling layers are used to perform max pooling. Input size is fixed due to the presence of fully connected layers. The input size is mentioned at most of the places as 224x224x3 but due to some padding which happens it works out to be 227x227x3 AlexNet overall has 60 million parameters.

4.3 IMPLEMENTATION

For the detection of cricket activities, first the dataset was not readily available for training the model.It was created from cricket match videos from youtube by taking screenshots from those videos. This dataset comprises variety of cricket occurences.It has a total of 3200 images.Each class contains images taken from varying angles to help train the model for general cases.Next step is the preprocessing.To prepare raw data in a format that the network can accept, preprocessing the data is a common first step in the deep learning workflow. This is done in order to make the data fit our model. Before the dataset images and labels could be used to train the model, they had to be processed. Because our dataset comprises images of various sizes, scaling is required in order for them to interact with our model and to be of the same dimensions. As a result, all of the photos have been reduced to 224X224 pixels. Transfer learning is applied on models pre-trained with imagenet dataset to decrease and eliminate data redundancy, and imagenet stats are used to normalise the data.Data augmentation is also done here.It is a technique for adding slightly changed copies of current data or newly created synthetic data from existing data to expand the amount of data. To be effective, neural networks require a large amount of data to work with. Since the dataset is handcrafted, augmentation is performed to expand it. Initialize the augmentation object for the training set using random flips (horizontal flip, vertical flip), zoom in, zoom out, lighting, and so on for the augmentation component.After this CNN models are built.Metrics are passed to measure the quality of the model's predictions using the validation set from the dataloader.Accuracy metric is passed ,as accuracy is calculated by a number of correctly classified examples divided by total classified examples including both correct and incorrect predictions.Fastai offers many architectures to use from which makes it very easy to use transfer learning.Convolutional neural network models can be created using the pre-trained models that work for most of the datasets.Figure 4.3.1 represents the building of CNN models.

```
#resNet50

In [10]: learn = cnn_learner(data, models.resnet50, metrics=accuracy)

#resNet101

In [11]: learn = cnn_learner(data, models.resnet101, metrics=accuracy)

#resNet34

In [12]: learn = cnn_learner(data, models.resnet34, metrics=accuracy)

#vgg16_bn

In [13]: learn = cnn_learner(data, models.vgg16_bn, metrics=accuracy)

#alexnet

In [14]: learn = cnn_learner(data, models.alexnet, metrics=accuracy)
```

Fig 4.3.1 : Building of CNN models

After that comes training and testing.For splitting the dataset into training and testing set,ImageDatabunch is used.It is a component of fastai library which is used to represent an image into testing and training.The training had training loss, accuracy and timetable for each step. For all the steps in the steps in the training, there were subsequent steps for testing as well. That's how the model was able to learn from mispredictions and gradual processing of the images. Variations of photos were provided in the testing dataset.

Optimization techniques (One Cycle Policy) were applied not to underfit the data.The One cycle policy gives very fast results when training complex models. Figure 4.3.2 depicts training our model with one cycle policy.

```
In [16]: learn.fit_one_cycle(5)
```

Fig 4.3.2 : One cycle policy

It follows the Cyclical Learning Rate (CLR) to obtain faster training time with regularization effect but with a slight modification. Picking the right learning rate at different iterations helps model to converge quickly. Feature extraction is done as a next step.There are many features in an image, and not all of them contribute to model training. Background features are unneeded in our instance because we just require features from the player. Our primary aim is to observe the actions of the player or umpire. They are the main components to be considered for detecting the activities in cricket.Classification is completed after training with one cycle policy and confusion matrix is plotted.A confusion matrix is a table that is often used to describe the performance of a classification model or classifier on a set of test data for which the true values are known.Figure 4.3.3 represents the confusion matrix plotted for those cricket activities.

```
In [28]: interp = ClassificationInterpretation.from_learner(learn)
```

```
In [29]: interp.plot_confusion_matrix()
```

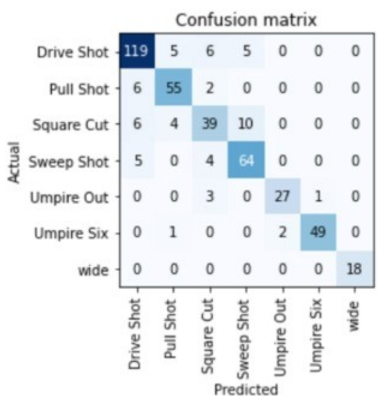

Fig 4.3.3 : Confusion matrix

Then it is evaluated using performance measures such as precision, recall, f1 score and support.The prediction of specific cricket activity is done using using specific libraries like matplotlib,Python Image Library.By specifying the image size,the test images are iterated.Then prediction is done 3 times in order to get the best and the probabilities are picked.Since the probability values are between 0 to 1,it is multiplied by 100.The class name and the probability score is given as output and it is plotted.A comparative research will be conducted to determine which model produces the highest accuracy rate.The comparative research comprises of the CNN algorithms namely Resnet34, Resnet50, Resnet101, Alexnet and VGG16.

The models are evaluated based on precision,recall and F1 score. Precision is one indicator of a machine learning model's performance – the quality of a positive prediction made by the model. Precision refers to the number of true positives divided by the total number of positive predictions,that is the number of true positives plus the number of false positives.The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples.The F1 score is a machine learning metric that can be used in classification models.Precision and Recall are the two most common metrics that take into account class imbalance. They are also the foundation of the F1 score.Precision is the first part of the F1 Score.Recall is the second component of the F1 Score. The goal of the F1 score is to combine the precision and recall metrics into a single metric. At the same time, the F1 score has been designed to work well on imbalanced data.The F1 score is defined as the harmonic mean of precision and recall.A model will obtain a high F1 score if both Precision and Recall are high;A model will obtain a low F1 score if both Precision and Recall are low;A model will obtain a medium F1 score if one of Precision and Recall is low and the other is high.The F1 Score is the

2*((precision*recall)/(precision+recall)).

Table 4.3.1 depicts the model ResNet50 on various evaluation metrics. The evaluation metrics include precision,recall and F1 score.It has been evaluated for drive shot,pull shot,square cut,sweep shot,umpire out,umpire six and wide.

	Precision	Recall	F1-score
Drive shot	0.98	0.99	0.98
Pull shot	0.99	0.99	0.99
Square cut	0.98	0.92	0.95
Sweep shot	0.98	1.00	0.99
Umpire out	1.00	1.00	1.00
Umpire six	1.00	1.00	1.00
Wide	1.00	1.00	1.00

Evaluation table for ResNet50

Table 4.3.1 : Evaluation metrics for Resnet50

Table 4.3.2 depicts the model ResNet34 on various evaluation metrics. Precision, recall, and F1 score are among the evaluation metrics.Drive shot,pull shot, square cut, sweep shot, umpire out, umpire six, and wide have all been examined.

	Precision	Recall	F1-score
Drive shot	0.98	0.98	0.98
Pull shot	0.97	0.99	0.98
Square cut	0.98	0.94	0.96
Sweep shot	0.95	0.98	0.97
Umpire out	0.96	0.85	0.90
Umpire six	0.91	0.88	0.89
Wide	0.88	1.00	0.94

Evaluation table for ResNet34

Table 4.3.2 : Evaluation metrics for Resnet34

Table 4.3.3 depicts the model ResNet101 on various evaluation metrics.Precision, recall, and F1 score are three evaluation metrics.Drive shot, pull shot, square cut, sweep shot, umpire out, umpire six, and wide have all been tested on it.

	Precision	Recall	F1-score
Drive shot	0.97	0.97	0.97
Pull shot	0.93	0.91	0.92
Square cut	0.74	0.83	0.78
Sweep shot	0.88	0.90	0.89
Umpire out	0.92	0.81	0.86
Umpire six	0.89	0.88	0.88
Wide	0.96	1.00	0.98

Evaluation table for ResNet101

Table 4.3.3 : Evaluation metrics for Resnet101

Table 4.3.4 depicts the model VGG16 on various evaluation metrics.The evaluation metrics include precision,recall and F1 score.Drive shot, pull shot, square cut, sweep shot, umpire out, umpire six, and wide have all been studied.

	Precision	Recall	F1-score
Drive shot	0.97	0.98	0.98
Pull shot	0.97	0.95	0.96
Square cut	0.92	0.92	0.92
Sweep shot	0.95	0.97	0.96
Umpire out	0.88	0.78	0.82
Umpire six	0.88	0.90	0.89
Wide	0.92	1.00	0.96

Evaluation table for VGG16

Table 4.3.4 : Evaluation metrics for VGG16

Table 4.3.5 depicts the model Alexnet on various evaluation metrics.Precision, recall, and F1 score are some of the evaluation metrics.Drive shot,pull shot, square cut, sweep shot, umpire out, umpire six, and wide have all been examined.

	Precision	Recall	F1-score
Drive shot	0.79	0.86	0.82
Pull shot	0.75	0.68	0.71
Square cut	0.60	0.63	0.62
Sweep shot	0.81	0.76	0.79
Umpire out	0.86	0.70	0.78
Umpire six	0.85	0.71	0.78
Wide	0.89	0.77	0.83

Evaluation table for Alex net

Table 4.3.5 : Evaluation metrics for Alexnet

In this chapter the implementation is discussed in detail. The next chapter will be dealing with the results of the work and the performance analysis.

CHAPTER 5

RESULTS AND PERFORMANCE ANALYSIS

This section emphasizes on the achieved results and subsequently discusses the findings of proposed model. In this paper, a distinct approach is proposed to detect the cricket activities using deep learning. Model is trained on our own dataset which consists of different images captured in different angles and very much able to detect and distinguish incidents of cricket. With the use of a CNN, this project attempts to classify images based on cricketing activities. The goal is to identify the activities that occur during a cricket match. It comprises multiple symbols as well as several cricket strokes played by the cricketers. ResNet50, ResNet101, ResNet34, VGG16, and AlexNet are used to do this. A fresh dataset is established for the project. This collection includes a variety of cricket match events. Because the dataset contains images of varied sizes, scaling is required for them to interact with our model and be of the same dimensions before they may be utilised to train the model. As a result, all of the images have been resized to 224X224 pixels. To reduce and eliminate data redundancy, transfer learning is used on models pre-trained with the imagenet dataset, imagenet stats are used to normalise the data, and augmentation is done to increase the size of the dataset by initialising the augmentation object for the training set with random flips (horizontal flip, vertical flip), zoom in, zoom out, lighting, and so on. An ImageDataBunch was constructed using an imagenet style dataset in path with train and test subfolders after binding the train, valid, and test dataloaders in a data object. Training begins when the label map is initialised with 7 classes. Each stage in the training had a training loss, validation loss, accuracy, and timeline. There were testing (validation) steps for each phase in the training. That's how the model was able to learn from its mistakes and gradual image processing. The testing dataset included many

Figure 5.1: Detection of Cricket activity

image variations. To avoid underfitting the data, optimization approaches (One Cycle Policy) were used. There are several elements in an image, but not all of them help to model training. Background characteristics aren't required because we just require player-specific features. The player or umpire is our primary focus. The models are already fairly good at extracting features thanks to the application of transfer learning. They can figure out which features are required and use dropout to reduce the amount of options. Following these steps, the model will be ready to detect cricket behaviours, and a comparative research will be conducted to determine which model produces the highest accuracy rate. Figure 5.1 shows the output of the project, the model has classified the images into a category of cricket activities. Given a test image containing a specific cricket activity,the model classifies and detects the kind of cricket activity and gives output which explains the 3 most promising cricket activity with its accuracy rate.

In this project the model has been proposed to identify 7 kinds of incidents from the images which lack some more incidents occurring in a cricket match. In future this project can be developed in such a way that the model can detect every event and players also by marking their special and individual stances from not only the images but also from videos in real time and mention like subtitles.

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