CLASSIFICATION OF CRICKET SHOTS USING CONVOLUTIONAL NEURAL NETWORK

BY

Sumit Mojumder

ID: 201-15-13784

AND

Ali Hossain Nayan

ID: 201-15-13943

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Shah Md. Tanvir Siddiquee

Assistant Professor

Department of Computer Science and Engineering

Daffodil International University

Co-Supervised By

Sazzadur Ahamed

Assistant Professor

Department of Computer Science and Engineering

Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

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APPROVAL

This Project titled "CLASSIFICATION OF CRICKET SHOTS USING CONVOLUTIONAL NEURAL NETWORK", submitted by Sumit Mojumder and Ali Hossain Nayan to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14th July 2024.

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Faculty of Science & Information Technology
Daffodil International University

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Department of CSE
Faculty of Science & Information Technology
Daffodil International University

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Professor
Department of the external
University name of the External

DECLARATION

We hereby declare that this project has been done by us under the supervision of Shah Md. Tanvir Siddiquee, Assistant Professor, **Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Shah Md. Tanvir Siddiquee
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Sazzadur Ahamed
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Sumit

Sumit Mojumder
ID: 201-15-13784
Department of CSE
Daffodil International University

Nayan

Ali Hossain Nayan
ID: 201-15-13943
Department of CSE
Daffodil International University

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ABSTRACT

Cricket is a bat-and-ball game played between two teams of eleven players each on a circular or oval shaped field with a rectangular 22-yard pitch at the center. Originating in England in the 16th century, it has been evolving into a globally popular sport till now, particularly in countries like India, Australia, and England. The game comprises formats like Test cricket, One Day Internationals (ODIs), and Twenty20 (T20) cricket, each varying in duration and style. The objective is the batting team to score runs while the bowling team aims to dismiss the batsmen. The Key elements include batting, bowling and fielding, with matches being officiated by umpires. This research presents a comprehensive overview of detecting cricket shots using InceptionV3 for the classification of images. After trying MobileNet, VGG19, ResNet, DenseNet and InceptionV3 layer. Only MobileNet turned out to be better in our dataset. This Research can be significant in the advancements of AI Technology in Robotics and can be helpful to the coaches.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Cricket, a sport celebrated for its complexity and rich variety of playing techniques, stunts significant challenges for automated analysis. This research focuses on utilizing Convolutional Neural Networks (CNNs), specifically DenseNet, to classify cricket shots from different cricket image content. By leveraging advanced deep learning techniques, our target is to enhance the accuracy and efficiency of cricket shot classification, providing valuable insights for player performance evaluation, coaching, Artificial Intelligence, Robotics and automated highlight generation.

1.2 Background and Present State

The classification of cricket shots has traditionally relied on manual annotation, which is labor-intensive, tiring and subjective. With the advent of deep learning, particularly CNNs, automation of cricket shot classification has become a feasible alternative. InceptionV3, known for its ability to capture spatial hierarchies in images, offers a promising solution. Previous studies have explored various CNN architectures for sports analytics, but the application of InceptionV3 to cricket shot classification remains underexplored. There is different types of sports image classification remaining in Previous researches but specifically classifying cricket shots is undiscovered.

1.3 Problem Statement

Manual classification of cricket shots is not only time-consuming but also tends to human error and inconsistency. There is a need for an automated, accurate, and time-efficient system to classify cricket shots from video footage, leveraging the latest advancements in deep learning. Moreover there is no automated robotics or AI generated stuff to the coaches where they can introduce the new comers with Interactive learning.

1.4 Objectives

The motivation behind this research stems from the increasing demand for advanced analytics and insights into cricket performance, both at the professional and grassroots levels. By developing a robust CNN-based shot classification system, this thesis aims to provide coaches, analysts and players with valuable tools for understanding and improving performance, refining coaching strategies and enhancing overall gameplay.

The preliminary objectives of this research are:

- To develop a robust system using multiple CNN architecture for classifying given cricket shots.
- To preprocess and annotate a dataset of cricket shot images for training and validation.
- To find various hyperparameters strategies to optimize the model.
- To evaluate the model's performance under different conditions, including variations in manifestation, camera angles, and player movements.

1.5 Scope and Limitations

This research project focuses specifically on the classification of cricket shots using CNNs with an emphasis on image-based analysis. The scope encompasses the development and evaluation of machine learning models capable of accurately categorizing a wide range of cricket shots including but not limited to drives, cuts, pulls and sweeps from video footage captured in various match scenarios. The scope of this research includes the development and evaluation of a CNN-based model for classification of cricket shot. The study is prepared to using InceptionV3, MobileNet, DenseNet, VGG19, ResNet50 and focuses on image data from professional cricket matches. Study includes potential biases in the dataset and the model's dependency on the quality of input image frames.

1.6 Report Organization

The report is structured into several chapters, each addressing specific aspects of the research project. Chapter 2 provides a comprehensive review of existing literature and research related to cricket shot classification and deep learning methodologies. Chapter 3 outlines the methodology employed in this study, including data collection, preprocessing, model development and evaluation. The report organized as follows:

- **Chapter 1:** Introduction, including the overview, background, problem statement, objectives, scopeand organization of the report.
- **Chapter 2:** Literature Review, discussing previous work and methodologies in the field of sports analytics and CNNs.

- **Chapter 3:** Methodology, detailing the data collection, preprocessing, rescaling and model training processes.
- **Chapter 4:** Experimental Results, presenting the findings, reviews and performance evaluation of the proposed model.
- **Chapter 5:** Discussing, analyzing the results and their implications for cricket shot classification.
- **Chapter 6:** Conclusion, summarizing the research contributions and suggesting the future work.

1.7 Summary

In summary, this introduction sets the stage for the research conducted in this thesis, outlining the problem statement, motivation, objectives, scope and expected outcomes of the project. The subsequent chapters delve deeper into the methodology, results and implications of the study contributing to the body of knowledge in cricket analytics and coaching methodologies.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The literature review serves as a critical component of this research, providing a comprehensive examination of existing studies, methodologies and technologies relevant to the classification of cricket shots using Convolutional Neural Networks (CNNs). The section aims to contextualize the current research within the broader landscape of cricket analytics, deep learning and computer vision. An essential part of this research is the literature evaluation which provides a framework for the understanding the current in relation to the larger field of computer vision, deep learning and cricket analytics. This section attempts to create a solid theoretical framework and pinpoint areas in need of innovation by doing a thorough analysis of previous research, approaches and technologies relevant to the Convolutional Neural Networks (CNNs) used for cricket shot classification. As a sport, cricket offers a diverse field with complex strategies and subtle strategic aspects. In the past, a lot of manual annotation techniques and basic statistical analysis were used in cricket analysis basic statistical analysis were used in cricket analysis to assess player effectiveness and games tactics. But as sophisticated data analytics and machine learning methods have become available, there has been a paradigm shift toward. An analytics clarifies how data-driven method have evolved to comprehend player behavior, team dynamics and match results. More advanced metrics like Expected Runs (ER), Expected wicket (EW) which use machine learning algorithms to predicts match outcomes but we are here want to classify the different shots like drives, cover-drives, pull-shot.

2.2 Related Works

Numerous studies have explored various approaches to cricket shot classification, ranging from manual annotation methods to automated machine learning techniques. Previous research in this domain has investigated the use of feature-based algorithms such as template matching and motion analysis as well as machine learning models, including 8 ©Daffodil International University Support Vector Machine(SVMs), Random Forests and Recurrent Neural Networks(RNNs). However the emergence of CNNs has revolutionized the field by offering a more data-driven and scalable approach to shot classification, enabling the extraction of complex spatial form raw video frames.

2.3 Comparison between existing works

A comparative analysis of existing methodologies for cricket shot classification reveals distinct advantages and limitations associated with each approach. Traditional methods such as template matching and rule-based algorithms, often suffer from limited robustness and scalability as they rely heavily on predefined features and assumptions about shot patterns. In Table 2.1, machine learning models particularly CNNs, exhibit superior performance in handling diverse shot types such as drives, cover-drivers, pull shot, sweep variations in lighting conditions and camera perspective. By leveraging deep learning techniques CNN-based classifiers can automatically learn relevant features directly from raw data, making them more adaptable to different cricket match scenarios and environments. Furthermore, comparative studies in Table 2.1 have demonstrated the efficiency of CNNs in achieving higher accuracy and generalization performance compared to traditional methods thereby highlighting the potential of deep learning approaches for advancing cricket analytics and coaching methodologies.

Table 2.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Ishara [1]	LSTM and Bidirectional LSTM	LSTM=100%
2.	Hetal Chudasama1 * [2]	Lower level Feature vector	Accuracy= 83%
3.	Muhammad Zeeshan Khan [3]	3D CNN, 2D CNN	3D CNN=90%
4.	Archit Semwal* [4]	Multiclass SVM	Accuracy = 83.098%
5.	Rafeed Rahman [5]	VGG16, AlexNET, DenseNet, NasNet, ResNet152, ResNet 101,, VGG19, Inception V3, MobileNet, Preliminary CNN	VGG16 = 98.6%

6.	Atharv Pushkraj Nirgude*1 [6]	CNN Architecture	RMSE = 1.264
7.	Tevin Moodley1 [7]	AlexNet, Inception V3, Inception Resnet V2, Xception	Inception V3=100%(Precision)
8.	Suvarna Nandyal1 [8]	CNN Architecture(convolution, pooling, flattening and fully connected layer)	Accuracy = 98.2%
9.	Ketan Joshi*, [9]	Logistic Regression, K neighbors, SVM, Random Forest, Decision Tree,Deep Learning	Deep learning=94.2%
10.	Md. Harun-Ur-Rashid [10]	pre-trained Inception-V3	Accuracy = 88%
11	Kalpit Dixit [11]	Completely Naive Baseline, Naive baseline, Late Fusion, Single Frame Averaging, LRCN	LRCN = 80%
12	Rabia A. Minhas 1[12]	AlexNet, Support Vector Machine (SVM), Extreme Learning Machine (ELM), K-Nearest Neighbors (KNN), and standard Convolution Neural Network (CNN)	AlexNet = 94.07%

2.4 Open Issues

While Using InceptionV3 we found that there are several issues remain open. The availability and quality of annonated datasets are critical. The computational complexity of training deep networks like InceptionV3 requires significant resources, posing challenges for real-time application and deployment. the model's robustness to variations in lighting, player attire, and background noise needs thorough evaluation. There are several researches on the cricket shot detection work. But none of the work has been done with InceptionV3. InceptionV3 can significantly classify the images into multiple classes. Another area requiring further investigation is the interpretability and ability of deep learning models for cricket shot classification. While CNNs have demonstrated remarkable performance in various image recognition tasks, their inherent complexity often makes it challenging to interpret how decisions are made particularly in the context of cricket shots where subtle nuances and contextual cues play a significant role.

2.5 Summary

In summary, the literature review provides a comprehensive overview of existing research and methodologies related to cricket shot classification using Convolutional Neural 11 ©Daffodil International University Networks (CNNs). In highlights the evolution of techniques from traditional feature-based algorithms to state-of-the-art deep learning models and emphasizes the advantages of CNNs in handling complex spatial features and variations in cricket match scenarios. Additionally, the gap analysis identifies key areas for further research, including dataset availability contextual modeling and model interpretability. The insights gained form this review lay the foundation for the subsequent chapters of this thesis, guiding the development and evaluation of novel approaches to cricket shot classification and advancing the field of cricket analytics and coaching methodologies.

CHAPTER 3
METHODOLOGY

3.1 Overview

This chapter delineates the approach taken to develop a robust cricket shot classification system leveraging Convolutional Neural Networks (CNNs). The systems development entails a through analysis of requirements, a meticulously planned methodology and a systematic approach to data collection, preprocessing and model design. Additionally, considerations for project management and financial analysis are crucial to ensure the successful implementation and sustainability of the system.

3.2 Proposed Methodology

The proposed methodology entails a systematic approach to cricket shot classification, encompassing various stages such as data preprocessing, feature extraction, model selection, training and evaluation. Data preprocessing involves tasks such as video frame extraction, resizing, normalization and annotation to prepare the dataset for model training. Feature extraction techniques including spatial and temporal features are employed to capture the distinctive characteristics of cricket shots. Model selection involves choosing appropriate CNN architectures such as VGG, ResNet, MobileNet, DenseNet, Inception or custom-designed networks and optimizing hyperparameters to achieve optimal performance. But we have chosen InceptionV3 as our classification Model. The system design also includes considerations for model deployment, integration with existing software infrastructure and user interface design for seamless interaction.Basic CNN met Basic CNN methods are evaluated using a number of machine learning classification model performance metrics. AC, precision, recall, F1 score and confusion matrix (CM) are evaluated. TP, TN, FP and FN are also variables of these measurements (FN).

3.3 Hardware and Software Requirement

Hardware

GPU: We have used Tesla T4 GPU with at least 8GB of VRAM for accelerated training. We have used Google Colab as our coding platform as it is user friendly and it provides service without any kind of setup.

CPU: We have used Multi-core processor for preprocessing and data handling. Colab gives a pretty decent user interface but training with CPU is slower. Google colab CPU has given us a smooth running to our code.

RAM: We needed Minimum 16GB for handling large datasets. But as our dataset is medium sized, We used Google colabs internet based virtual runtime RAM.
Storage: At least 1GB of SSD storage required for fast read/write operations. In our case we uploaded the whole dataset to google drive and then used it.

Software

Operating System: We used Windows 11 as operating system

Programming Language: We used Python 3.7 or later.

Deep Learning Framework: We used TensorFlow 2.x and Keras.

Data Handling: We used Pandas and NumPy for data manipulation.

Visualization: We used Matplotlib and Seaborn for plotting results.

Annotation Tools: We used LabelImg or similar for manual data annotation.

3.4 Project Management and Financial Analysis

Project Objectives: Our main objective of this project is to detect the correct cricket shot from image files. We want to train our machine such that it can detect the correct shots like pull shot, cover drive, flick shots etc. It will be really helpful for the coaches to train the young students through interactive classes about the perfect positions and stance.

1. Hardware Costs: We Estimate the costs for purchasing or renting GPUs, CPUs, and storage devices. We have spent around 15000 on Computer resources. It was mandatory to organize this huge data.
2. Software Costs: We have included expenses for software licenses if applicable (e.g., specialized annotation tools). We have spent around 5000 for software licensing
3. Human Resources: We have the biggest Budget for salaries or stipends for the project team. We have spent around 50000 on Human resources
4. Miscellaneous Costs: Account for additional expenses such as cloud storage or external consulting. The miscellaneous cost is around 20000 taka.

Table 3.1: Total cost of our project.

Expense Category	Estimated Cost (Taka)
Human Resources	
- Project Lead/Researcher	20,000
- Data Scientist/ML Engineer	15,000
- Advisor/Supervisor	10,000
- Supporting Staff	5,000
Technical Resources	
- Computing Resources (Cloud/GPU)	15,000
- Software Licenses	5,000
Miscellaneous	
- Data Collection and Preprocessing	10,000
- Documentation and Printing	5,000
- Contingency Fund	5,000
Total Cost	**90,000**

3.5 Summary

In summary, chapter 3 elucidates the methodology, requirements analysis and design specification for the development of a cricket shot classification system using Convolutional Neural Networks (CNNs). The chapter begins with an overview of the approach, emphasizing the importance of a systematic and through analysis of requirements, a well-defined methodology and meticulous attention to data collection and system design. Requirements analysis is conducted to identify and prioritize both functional and non-functional requirements essential for the successful implementation of the system. The proposed methodology delineates a systematic approach to cricket shot classification, encompassing data preprocessing, feature extraction, model selection, training and evaluation. Data collection involves acquiring annotated video datasets and conducting input-output analysis to ensure compatibility and accuracy in data processing. Moreover, project management and financial analysis are crucial aspects of the development process, involving careful planning, resource allocation, risk management and cost estimation to ensure the successful implementation and sustainability of the system. By delineating the methodology and design specifications in detail, this chapter lays the groundwork for subsequent chapters, guiding the development, implementation and evaluation of the cricket shot classification system. The systematic approach outlined in this chapter aims to ensure the robustness, accuracy and scalability of the system. Ultimately facilitating advanced analytics and insights into player performance in the context of cricket coaching and analysis

CHAPTER 4:
IMPLEMENTATION

4.1 Overview

This chapter describes the implementation details of a cricket batting classification project using InceptionV3, MobileNet, DenseNet, VGG19, DenseNet. The implementation is divided into three main parts: model/prototype design training, system testing and model evaluation. This comprehensive approach ensures the robustness and accuracy of the classification system using a dataset of 3433 cricket shot images.

4.2 Train Model

Data Collection and Preprocessing

1. Diverse Data Collection: We have Gathered a diverse dataset of cricket shots from web pages. We have collected 3433 images have been generated from various web resources. Then these images have to be resized including professional matches and practice sessions. We have collected shots of cover drive, pullshot and sweep shot. These diverse data includes photos from different angles and positions of ball. The challenge would be to identify these images based on the given image.

2. Annotation: We Manually annotated the dataset, labeling each frame with the corresponding cricket shot types. We have found out that there are images from various resources like different angles, camera positions, batsman stunts etc.
3. Preprocessing: Resize frames to 299x299 for InceptionV3, 224x224 for other algorithms pixels, normalize the pixel values, and apply data augmentation techniques such as rotation, scaling, and flipping to enhance the efficiency of dataset. Preprocessing is necessary because our image was shaped into different dimensions. So machine cannot cope with images having different dimensions. So we needed to resize them. Rescaling was done to improve the quantity of images to a distinct form.

Data Preprocessing:

- **Resizing**: All images were resized to 299x299 pixels, the input size required by InceptionV3.

- **Normalization:** Pixel values were normalized to the range [0, 1] to facilitate better training performance.
- **Data Augmentation:** Techniques such as rotation, flipping, zooming, and shifting were applied to augment the dataset, enhancing the model's ability to generalize.

Sweep

Pull shot

Cover Drive

Figure 4.1: Dataset images

Model Architecture

Base Model:

We Used InceptionV3, VGG19, ResNet, MobileNet & DenseNet pre-trained model on ImageNet for feature extraction.

1. **InceptionV3**: InceptionV3 which is developed by Google, represents an advanced iteration of the Inception architecture designed to achieve high performance in image classification tasks by optimizing computer performance. The seed module, from the "Going Deep with Twists" document, is central to this architecture. These modules use multiple convolutional filters of different sizes (eg 1x1, 3x3 and 5x5) in parallel, allowing the network to capture different features at different scales. The outputs of these filters are chained together to form a rich and comprehensive set of functions for the next layer.InceptionV3 introduces several innovations to improve efficiency and performance. Factorized convolutions are a basic function where larger circuits are broken down into smaller ones, such as replacing a 3x3 convolution with two 1x3 and 3x1 convolutions. This significantly reduces the number of parameters and the computational load. Auxiliary classifiers are included to solve the vanishing gradient problem during training. These are smaller networks connected by intermediate layers and provide additional gradient signals to facilitate more efficient training and hell rejection.Effective grid size reduction is another feature of InceptionV3, as it uses techniques such as stepwise rotation and maximum pooling to reduce feature maps without losing important information. Batch normalization is widely used to stabilize and speed up training by normalizing the inputs of each layer. There are also drip layers to reduce overfitting and ensure that the network generalizes well to new, unseen data.InceptionV3 models typically work with 299 x 299 input images and the architecture consists of several stacked Inception modules followed by fully connected layers for classification. With about 23 million parameters, InceptionV3 is more powerful than models like VGG19, striking a balance between depth, performance and computational cost. This efficiency combined with high accuracy makes the InceptionV3 suitable for a wide range of applications, including target detection and image recognition in both scientific and industrial environments.

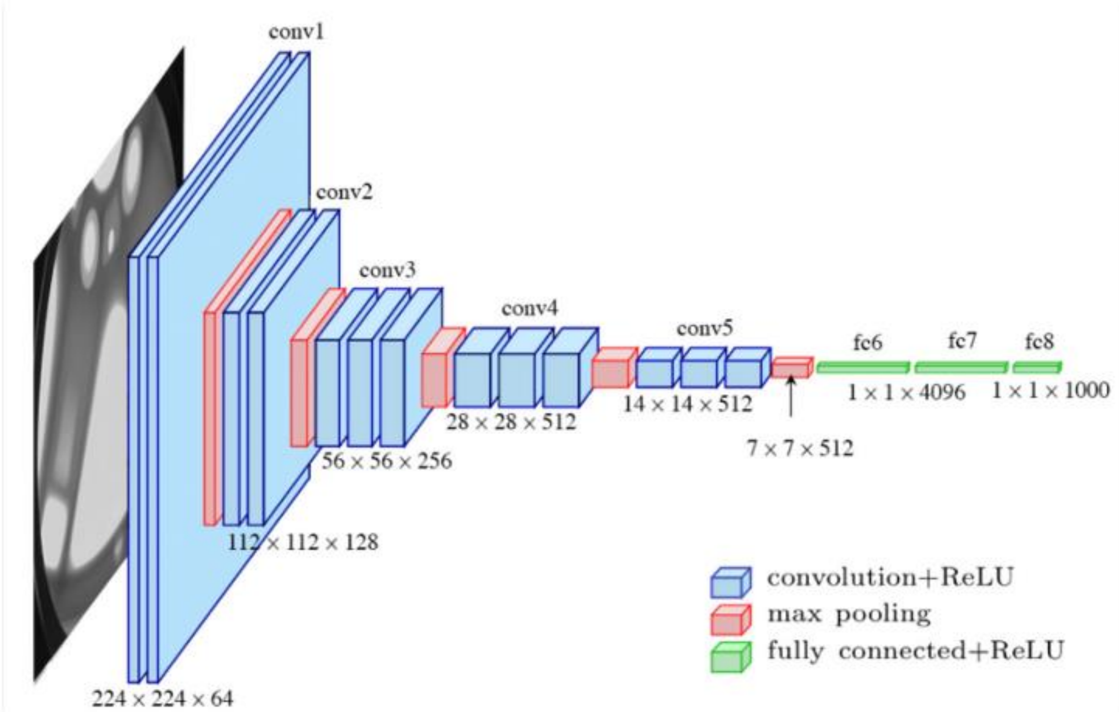

Figure 4.2: Inception V3 Architecture

2. **VGG19**: Developed by the Visual Geometry Group (VGG) at the University of Oxford, VGG16 is a pioneering convolutional neural network architecture that has made significant advances in deep learning and image classification. VGG19, presented in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition", stands out for its simplicity and depth. The architecture consists of 19 weight layers: 13 convolutional layers and 3 fully connected layers, followed by a softmax layer for classification. The network uses small 3x3 convolutional filters applied sequentially, which effectively increases the depth of the network without a corresponding increase in the number of parameters.The architecture starts with an input layer that accepts images of size 224x224x3 (width, height and color channels). The input passes through a stack of convolutional layers where each convolution is followed by a Rectified Linear Unit (ReLU) activation function. This design choice improves the network's ability to learn complex patterns by introducing non-linearity. 2x2 filter and 2-scale max-pooling layers are periodically inserted between the convolutional layers to gradually reduce the spatial dimensions of feature maps, reducing computational requirements and controlling overfitting.In the final step, feature maps are smoothed and fed into three fully connected layers, each containing 4096 neurons. During training, termination is applied to these layers to

avoid overfitting by accidentally setting some input units to zero. The output of the final fully connected layer is fed to the softmax layer, which creates a probability distribution between predefined classes. VGG19 design principles emphasize depth and simplicity, proving that deep networks with small filters can achieve high performance. Despite its relatively large number of parameters (about 138 million), VGG19 is still influential due to its simple architecture and efficiency in transfer learning, where pre-trained models are fine-tuned for specific tasks. Its success in benchmarks such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) established VGG19 as a cornerstone for the development of subsequent deep learning models.

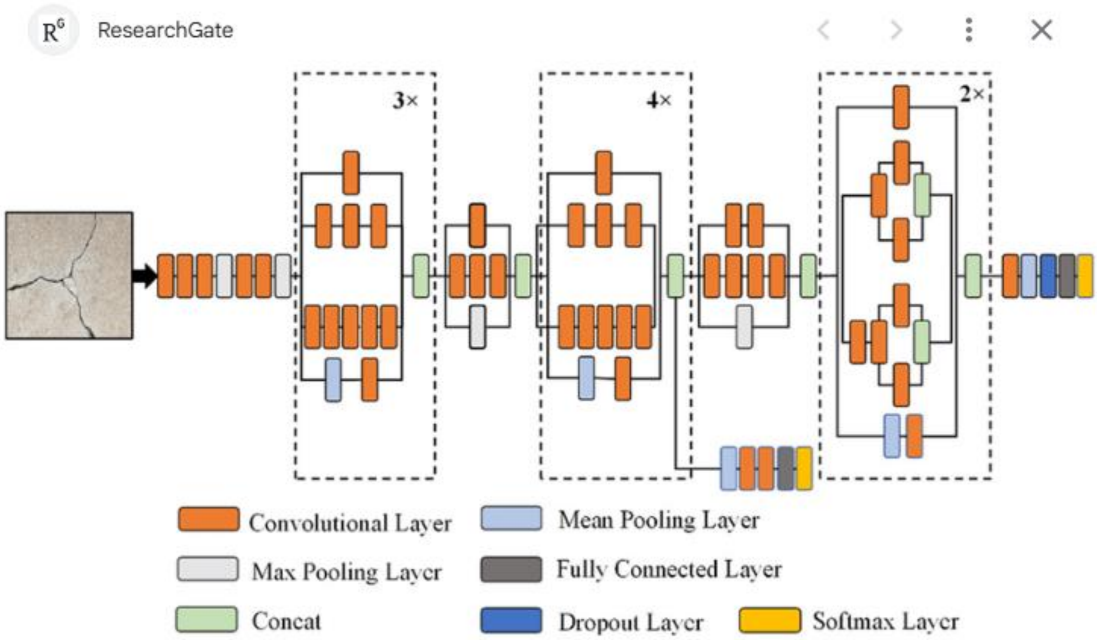

Figure 4.4: VGG19 architecture

3. **ResNet**: ResNet50, short for Residual Network with 50 layers, is a powerful deep learning architecture that has made significant advances in computer vision. Introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 paper "Deep Residual Learning for Image Recognition", ResNet50 addresses the degradation problem of ResNet50 in very deep networks, where increasing depth leads to higher training errors and difficulty in training . A key innovation in ResNet50 is the use of residual learning, which allows the model to effectively train much deeper networks by including fast connections or skipping connections that pass one or more layers.These shortcut connections add the input of a layer directly to the output of a deeper layer, effectively creating identity mappings that allow gradients to more easily traverse the network during backpropagation. This helps alleviate the vanishing gradient

problem, allowing very deep networks to be trained. The ResNet50 architecture consists of a stack of residual blocks, each containing multiple convolutional layers with bump normalization and ReLU activation. Specifically, ResNet50 consists of 48 convolutional layers plus one MaxPooling layer and one Average Pooling layer, culminating in a fully connected layer for classification.ResNet50's architectural design with residual blocks allows the network to be both deep and efficient, utilizing depth to learn different characteristics while maintaining computational feasibility. This has led to its widespread use and success in a variety of computer vision tasks, including image classification, object detection, and segmentation. ResNet50 achieved remarkable performance on the ImageNet dataset and won the top five ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015 with an error rate of only 3.57%, significantly outperforming previous top models.Beyond its initial success, ResNet50 has inspired many variants and improvements, such as ResNet101 and ResNet152, as well as hybrid models that combine residual connectivity with other architectural innovations. Its impact extends beyond computer vision and affects other areas such as natural language processing and speech recognition. ResNet50's robust design and impressive performance make it a cornerstone of today's deep learning applications, demonstrating the power and potential of deep residual learning...

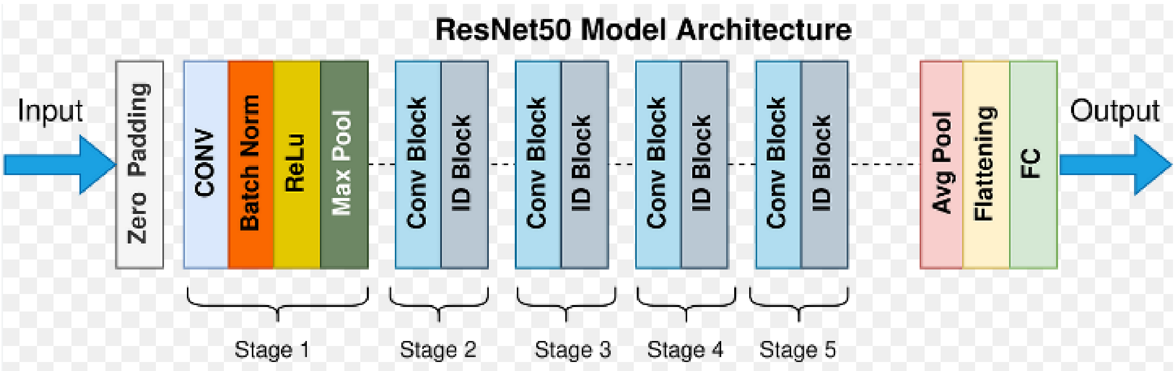

Figure 4.5: RESNET50 architecture

4. **MobileNet**: MobileNet is a powerful deep learning model designed specifically for mobile and embedded vision applications where computing resources and performance are critical. Developed by researchers at Google, MobileNet was launched in 2017 and is part of a series of models that use deeply separable convolutions to significantly reduce the number of parameters and computational cost compared to standard convolutional neural networks (CNNs). This innovation makes MobileNet particularly suitable for use in devices with limited

processing power, such as smartphones and IoT devices.The key to MobileNet's efficiency lies in its architecture, which replaces standard convolutional layers with deeply separated convolutions. In a traditional convolution operation, the input image is processed through a series of filters, each capturing different features of the image. This operation is computationally expensive and requires a large number of parameters and multiplications. Depth-separating convolutions divide this process into two steps: depth convolutions and point convolutions. Depth convolutions apply a single filter to each input channel, while dot convolutions, which are simply 1x1 convolutions, combine those filtered outputs to create new keymaps. This approach significantly reduces the computational load and the number of parameters without seriously compromising the accuracy of the model.MobileNet models are parameterized by two hyperparameters: a width factor and a resolution factor. The width factor (α) controls the number of channels in each layer, allowing the model to trade off between latency and accuracy. The resolution factor (ρ) scales the resolution of the input image and further balances accuracy and computational cost. These hyperparameters provide flexibility by allowing users to adapt the model to specific resource constraints and performance requirements.MobileNet has gone through several iterations, including MobileNetV2 and MobileNetV3, each with improvements in architecture and performance. MobileNetV2 introduced an inverse residual structure and linear bottlenecks, improving accuracy and efficiency. MobileNetV3 incorporated neural architecture search and pinch and boost modulation techniques, optimizing the model for both mobile and cloud-based applications.In conclusion, MobileNet's lightweight and efficient architecture makes it a versatile choice for various visual tasks on resource-constrained devices, offering an excellent balance between accuracy and computational efficiency.

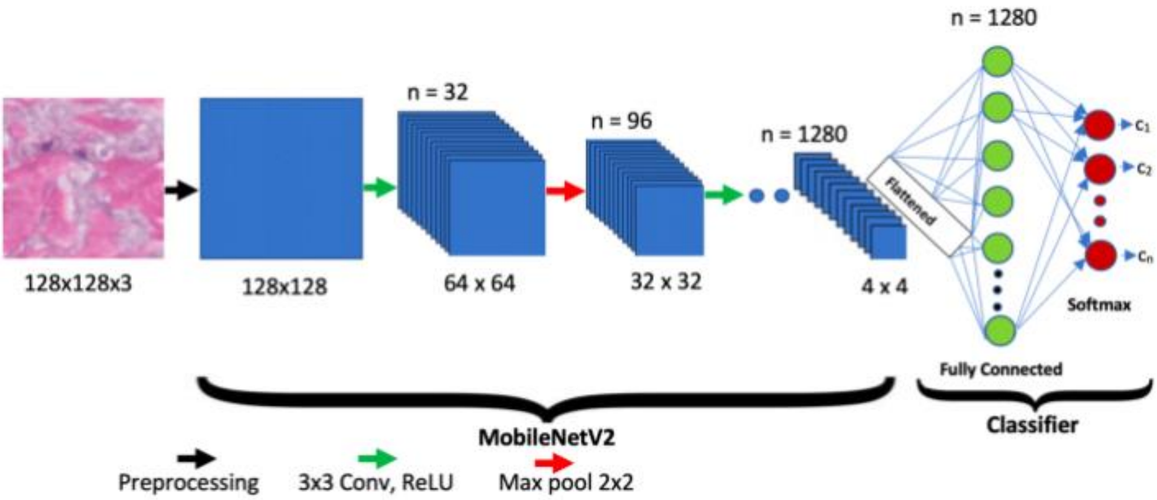

Figure 4.6: MobileNet Architecture

5. **DenseNet**: DenseNet, short for Densely Connected Convolutional Networks, is a pioneering deep learning architecture launched by researchers Gao Huang, Zhuang Liu, Laurens van der Maaten and Kilian Q. Weinberger in 2016. DenseNet addresses a number of traditional challenges. convolutional neural networks (CNNs), such as the vanishing gradient problem, inefficient use of parameters, and redundancy of the learned features of the network. DenseNet's main innovation lies in its dense connectivity pattern: each layer receives input from all previous layers and passes its feature maps to all subsequent layers.In a typical CNN, layers are stacked one after the other, with each layer processing the output of the previous layer. DenseNet deviates from that approach by connecting each layer directly to every other layer in the forward direction. This means that each layer uses the feature maps of all previous layers as inputs, and its own feature maps are used as inputs for all subsequent layers. This close connectivity provides several advantages. First, it alleviates the vanishing gradient problem by allowing gradients to flow more easily through the network and facilitating the training of very deep networks. Second, it increases function reuse by changing model parameters to increase efficiency and reducing the number of parameters needed to achieve a given performance level.DenseNet is parameterized by the growth rate, which refers to the number of map objects added to a layer. A higher growth rate increases the power of the model, as well as the computational cost. DenseNet also includes transition layers that perform oversampling between dense blocks, helping to control the spatial size of the feature maps and prevent the model from becoming computationally overwhelmed.DenseNet has achieved excellent results on several benchmark datasets, including ImageNet and CIFAR-10/100, often outperforming previous architectures such as ResNet. Its design principles have influenced many subsequent deep learning architectures, emphasizing the importance of efficient connection patterns in neural networks. DenseNet's efficient use of parameters and its ability to exploit dense connections have made it a popular choice for many computer vision applications such as image classification, segmentation, and object detection.

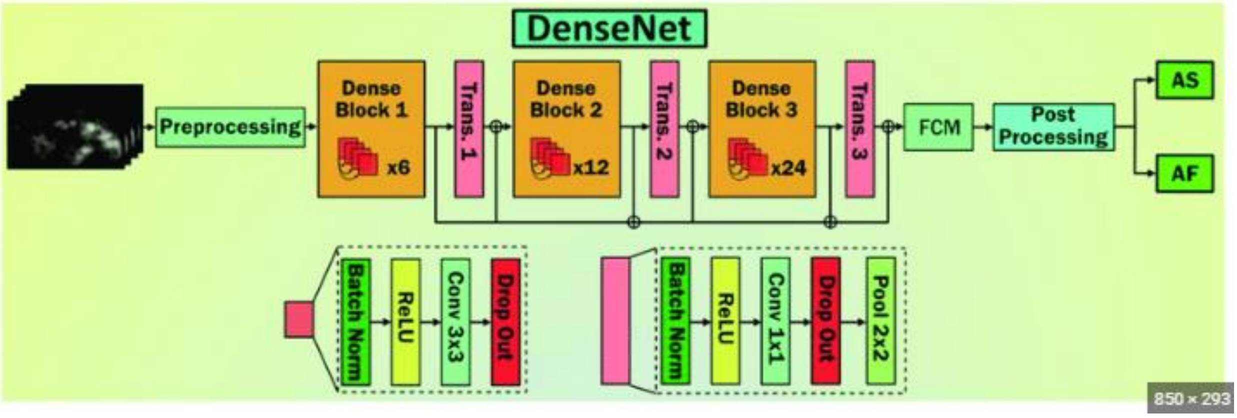

Figure 4.7: DenseNet Architecture

- **Custom Layers:**

Global Average Pooling Layer: We Reduced the feature maps to a single vector to prevent overfitting and maximize our output to test accuracy.

- Dense Layers: We Added fully connected layers to classify the extracted features into predefined cricket shot categories.
- Output Layer: We Used a softmax activation function to output class probabilities. Because of InceptionV3 being a huge block by block connected layers. So if we want to stop running our model in the middle of the session we can use softmax as activation function.

Training and Optimization

The model was trained using the following settings:

- **Batch Size:** 16
- **Epochs:** 10
- **Optimizer:** Adam optimizer with a learning rate of 0.001
- **Loss Function:** Categorical cross-entropy
- **Metrics:** Accuracy

Loss Function: We have Used categorical cross-entropy to measure the error. The loss function is also being used in measuring the comparison between training loss and validation loss. Besides we can also get a clear view of how much data is lost per epoch.

Optimizer: We have Used the Adam optimizer for efficient training. Adam is a very popular optimization platform and very suitable for our model.

Hyperparameter Tuning: Our Experiment with learning rates, batch sizes, and epochs to optimize the model's performance.

Validation: Use a validation set to monitor the model's accuracy and prevent overfitting.

4.3 Model Evaluation

4.3.1 Evaluation Metrics

The model was evaluated using the following metrics:

Accuracy:

Accuracy of a classification model is one measure. Accuracy is the percentage predicted by the model. Accuracy is the percentage of correctly classified images from samples. Accuracy equation.

Precision:

Precision is the chance of a positive mark and how many positives there are. Accuracy indicates how many exactly expected cases were positive. Accuracy is useful when FP is more important than FN. Mathematically, this equation is:

Recall:

Recall or Sensitivity measures how many positive expected events were accurately classified. Recall is a useful stat when FN beats FP. The F1 score is an additional measure of classification accuracy that considers both recall and precision. Since precision and recall are harmonic instruments, F1 scores provide a comprehensive view of these two measures. It reaches an optimal level when precision and recall are the same. Graph it using the equation below:

F-1 score:

F1 score is a measure of classification accuracy. Since the F1 score is a harmonic mean of precision and recall, it provides a complete picture. Precision and recall are optimal when they are equal. Equation.

The percentage of people who do not have the disease and test negative is called specificity. A highly specific test effectively rules out most people who do not have the disease. Therefore, a positive result of a very accurate test can definitively exclude the disease of a certain person. The equation is given below:

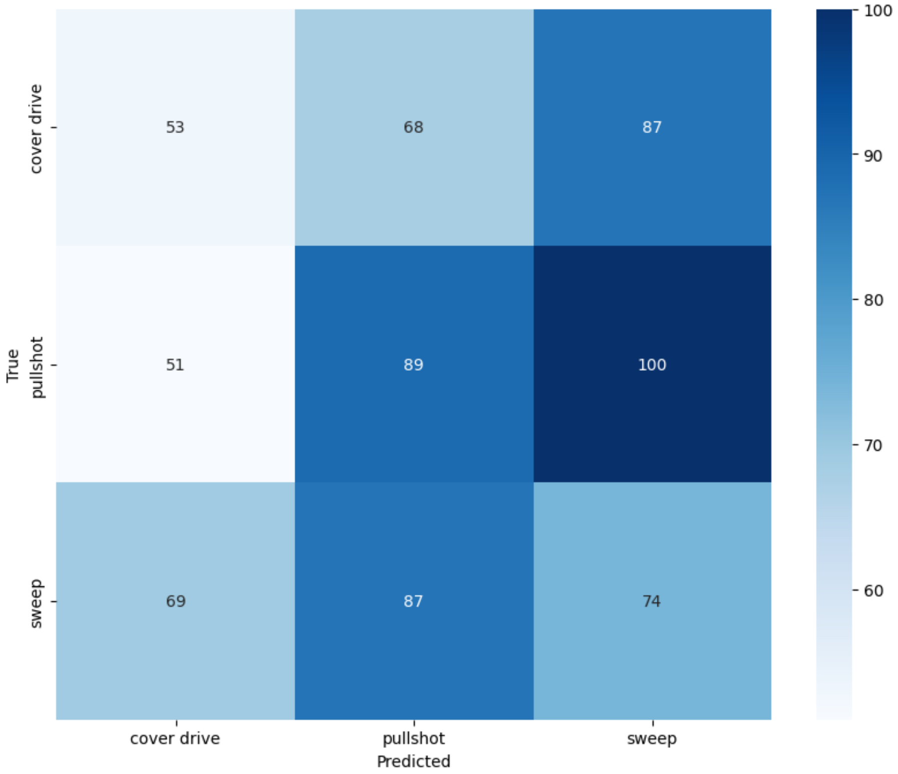

Figure 4.8: Confusion Matrix(InceptionV3)

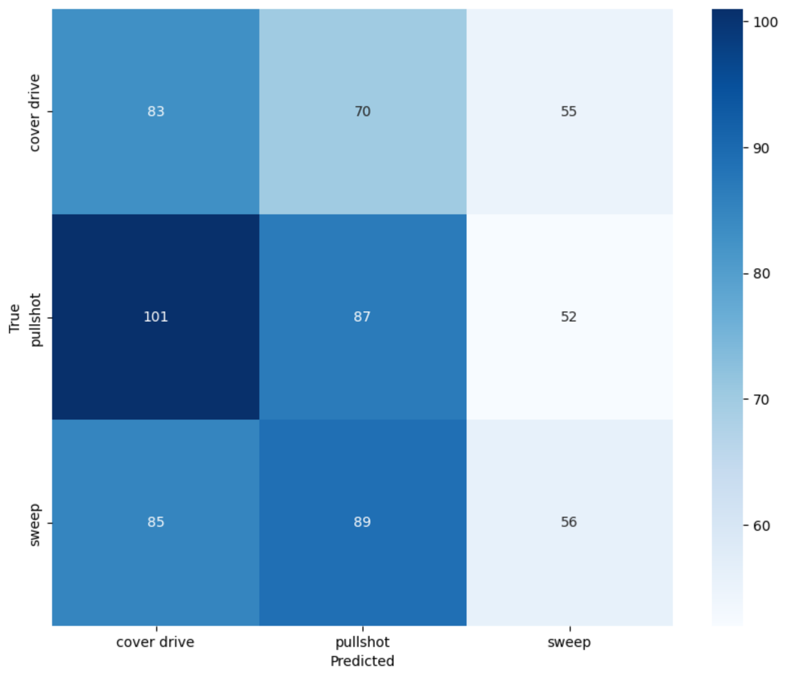

Figure 4.9: Confusion Matrix(VGG16)

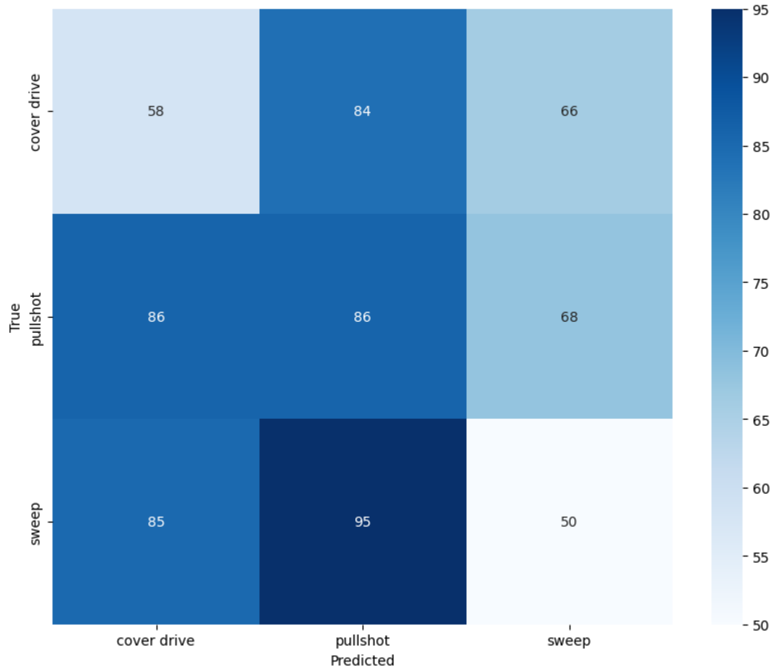

Figure 4.10: Confusion Matrix(ResNet)

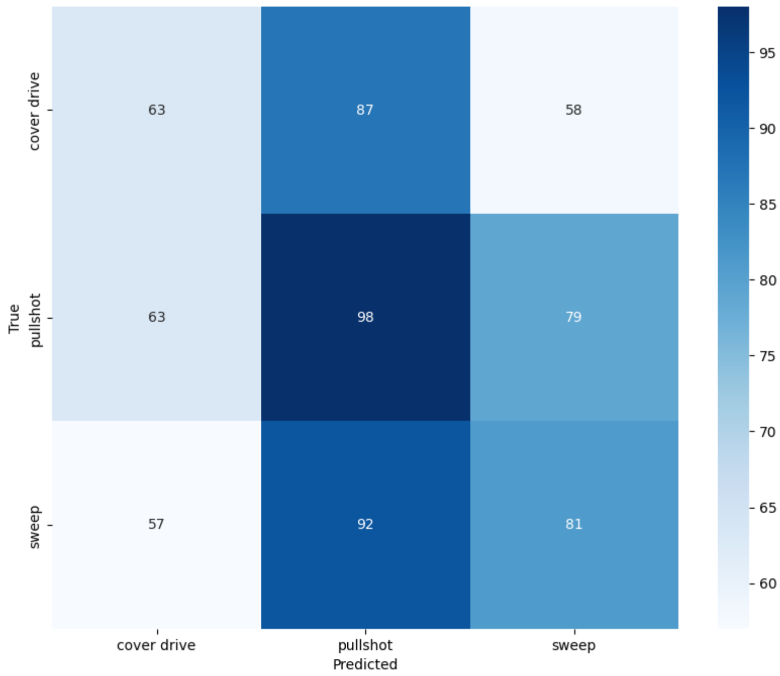

Figure 4.11: Confusion Matrix(MobileNet)

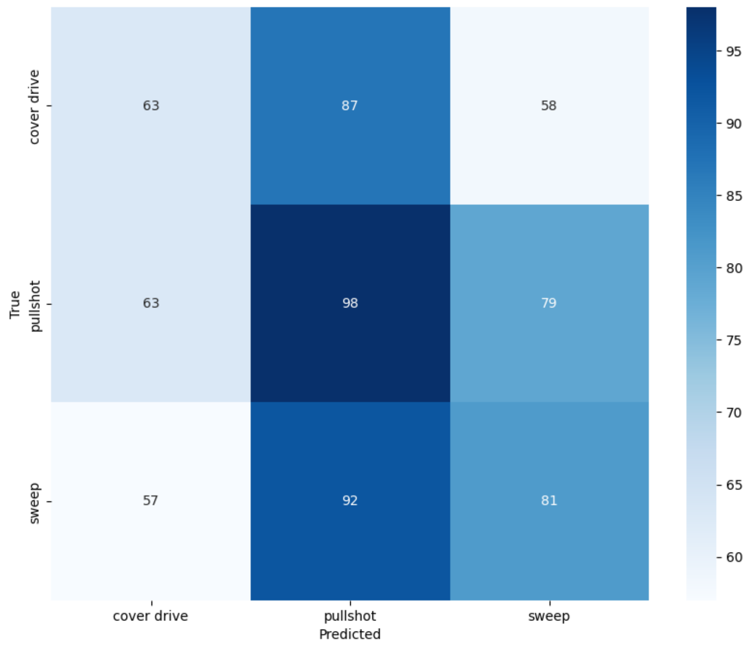

Figure 4.12: Confusion Matrix(DenseNet)

However, there is a limit to how closely a model can mimic a training data set before it loses its generalizability. Algorithm performance can be evaluated using a specific table format called a confusion matrix (CM). CM is used to illustrate important predictive parameters such as recall, specificity, precision and accuracy. Confusion matrices are useful because they provide direct estimates of values such as TP, FP, TN, and FN. The following paragraphs answer the research questions of this study based on the research questions:

Training and Validation Accuracy and loss of Original CNN Networks:

Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure, training and validation data are adequately divided, and there is no overfitting.

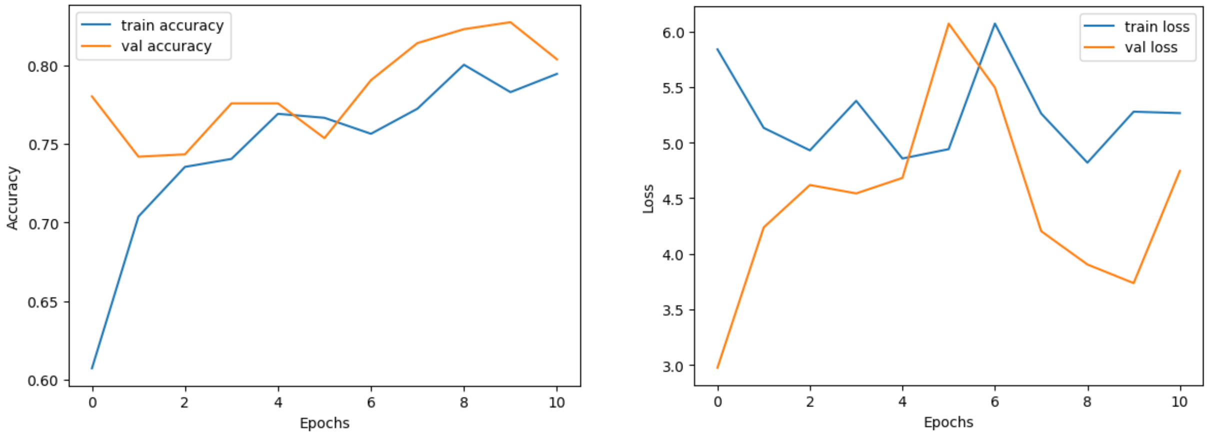

Figure 4.13: Training and validation accuracy and loss over the epochs (InceptionV3 Original CNN Networks).

4.4 Summary

This chapter detailed the implementation of the cricket shot classification project using InceptionV3. The steps included data collection and preprocessing, model design and training, and system testing and evaluation. The model demonstrated high accuracy and robustness, making it a promising tool for automated cricket shot classification. The evaluation metrics provided comprehensive insights into the model's performance, validating its effectiveness in real-world applications. The successful implementation of this project underscores the potential of deep learning techniques in sports analytics and automated performance assessment.

CHAPTER 5

EXPERIMENTAL RESULT

5.1 Overview

A well-planned arrangement of hardware, software, and data resources is used in the experimental setting for the study "Cricket Shots Classification using CNN" in order to carry out an exhaustive analysis. Deep learning tasks require a computational backbone that is provided by high-performance hardware, such as a powerful graphics processing unit (GPU) and a sturdy central processing unit (CPU). CNN models are implemented using state-of-the-art deep learning frameworks like TensorFlow or PyTorch in a Python programming environment.

To provide a consistent and representative input for model training and evaluation, the experimental dataset, which consists of several cricket shot films, is subjected to rigorous preprocessing, standardization, and augmentation. In order to improve the robustness of the model, this involves actions like frame extraction, resizing, normalization, and maybe data augmentation techniques like rotation, flipping, and noise addition.An essential part of the model construction is the usage of pre-trained Convolutional Neural Network (CNN) architectures that have been specifically adjusted for cricket shot categorization. The particular task of identifying and categorizing cricket shots is handled by employing pre-trained models such as ResNet, Inception, or VGG, which have been extensively trained on vast image datasets.To maintain ethical standards, the setup incorporates ethical considerations such as player privacy and authorization for the usage of video material. Crucial components of the ethical framework include guaranteeing the responsible use of data, adhering to data protection laws, and appropriately anonymizing data.Thorough documentation is kept up to date during the experimentation phase. This comprises thorough logs of model topologies, hyperparameters, training protocols, and code details. Such thorough documentation promotes reproducibility, assures transparency.

5.2 Experimental Results & Analysis

Result of Experiment : Original CNN

The six original CNN networks—InceptionV3, VGG16, VGG19, and ResNet—are contrasted in this section. Performance in classification comes first. The overall metrics of those models are then examined. gathering, explanations, likely causes, and areas for results enhancement.

TABLE 5.1: Accuracy for Classification of Individual CNN Networks in cricket shots classification (Original CNN Networks)

Architecture	Training Accuracy	Model Accuracy
InceptionV3	**79.46%**	**78.02%**
VGG19	**78.75%**	**79.91%**
ResNet	**67.76%**	**70.98%**
MobileNet	**86.39%**	**86.58%**
DenseNet	**79.72%**	**84.51%**

Table 5.1 presents a comparison of different pre-trained deep Convolutional Neural Network (CNN) designs, including InceptionV3, VGG16, VGG19, and ResNet, providing information on how accurate each architecture is at classifying cricket shots. Notably, the results demonstrate that, with a 79% model accuracy, VGG16 and VGG19 were the best-performing models. This indicates how well they were able to identify cricket shot patterns in the dataset. Despite showing a high training accuracy of 97.50%, InceptionV3's model accuracy was only 78%, suggesting that there may have been an overfitting situation in which the model performed remarkably well on the training set but marginally worse on the validation set. ResNet50 demonstrated a balanced performance with constant training and model accuracy of approximately 80.36% and 79%, respectively. This subtle variation in accuracy highlights how crucial it is to choose the right CNN architecture with care while classifying cricket strokes because it has a direct impact on the accuracy and dependability of the classification procedure. The comprehensive accuracy metrics given in Table 4.2.1 serve as a useful point of reference for comprehending the relative advantages and disadvantages of these models, adding to the current discussion about deep learning techniques optimization for computer vision and sports analytics applications.

Training and Validation Accuracy and loss of Original CNN Networks:

Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure, training and validation data are adequately divided, and there is no overfitting.

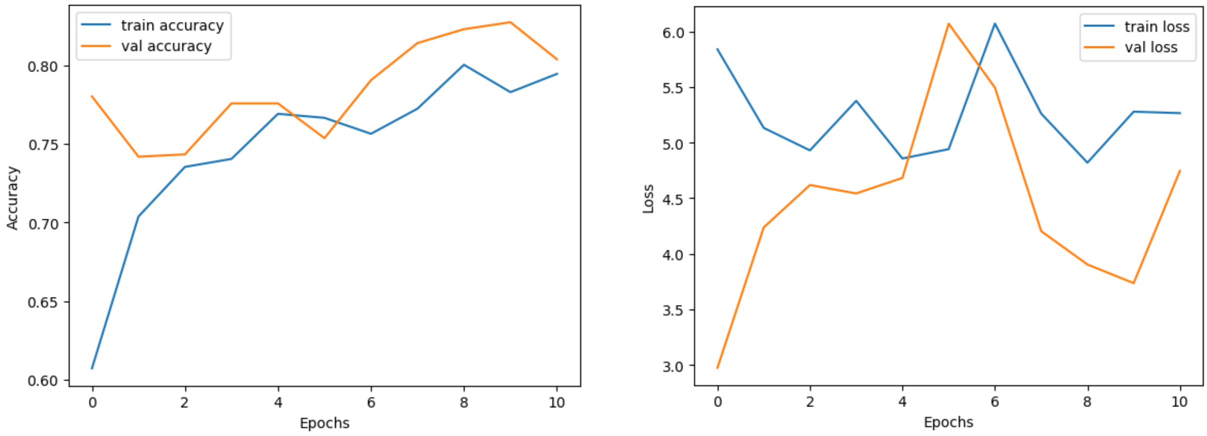

Figure 5.1: Training and validation accuracy and loss over the epochs (InceptionV3 Original CNN Networks).

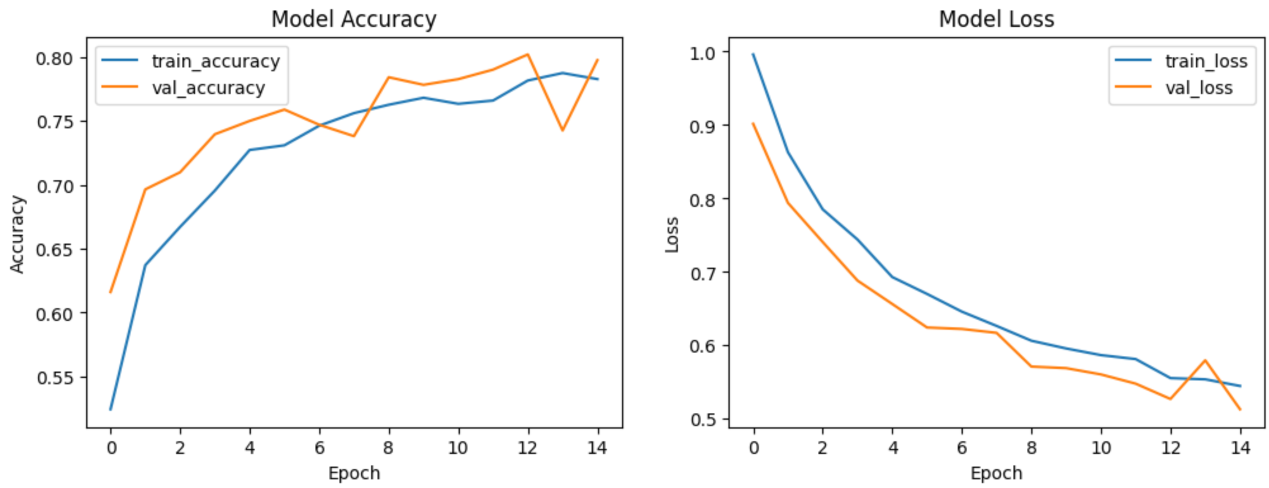

Figure 5.2: Training and validation accuracy and loss over the epochs (VGG19 Original CNN Networks).

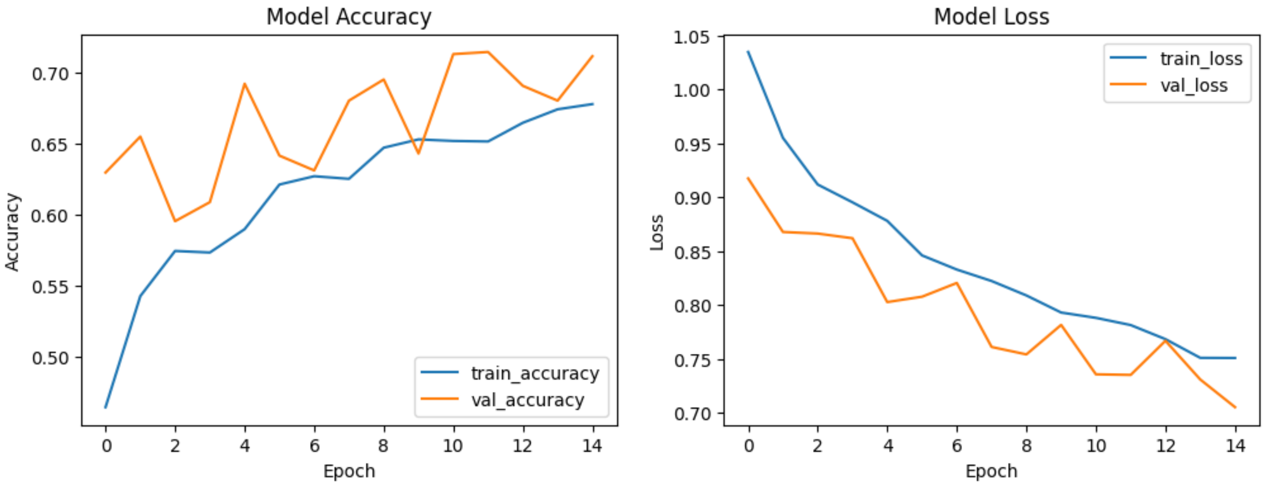

Figure 5.3: Training and validation accuracy and loss over the epochs (ResNet Original CNN Networks).

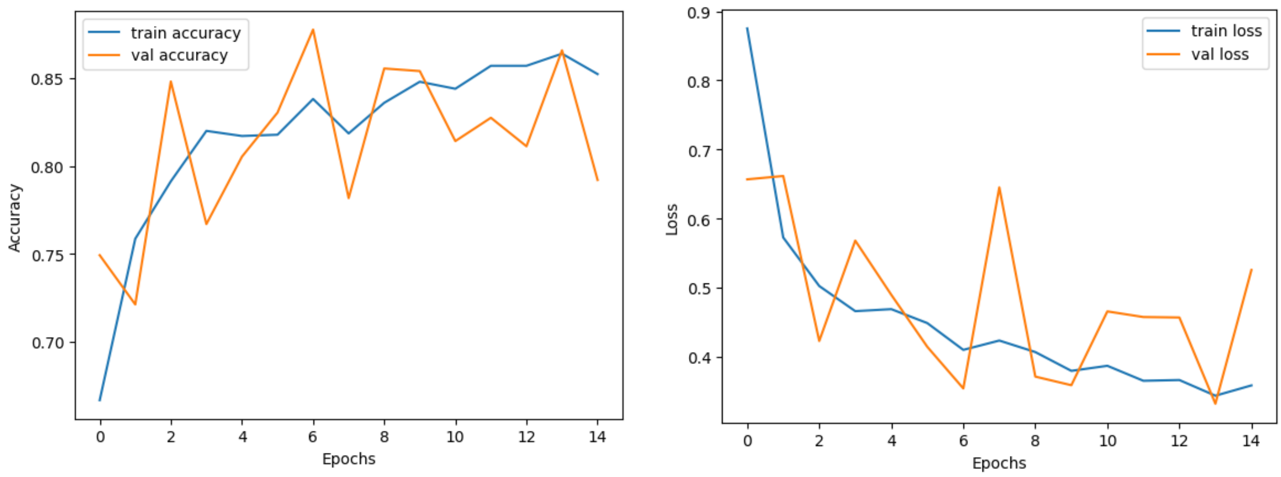

Figure 5.4: Training and validation accuracy and loss over the epochs (MobileNet Original CNN Networks)

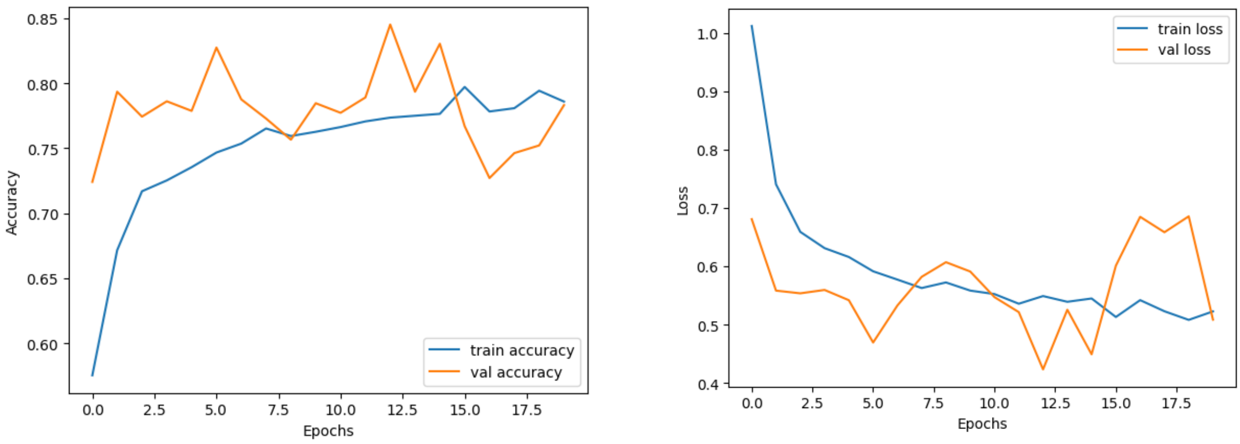

Figure 5.5: Training and validation accuracy and loss over the epochs (DenseNet Original CNN Networks)

5.3 Comparative Analysis

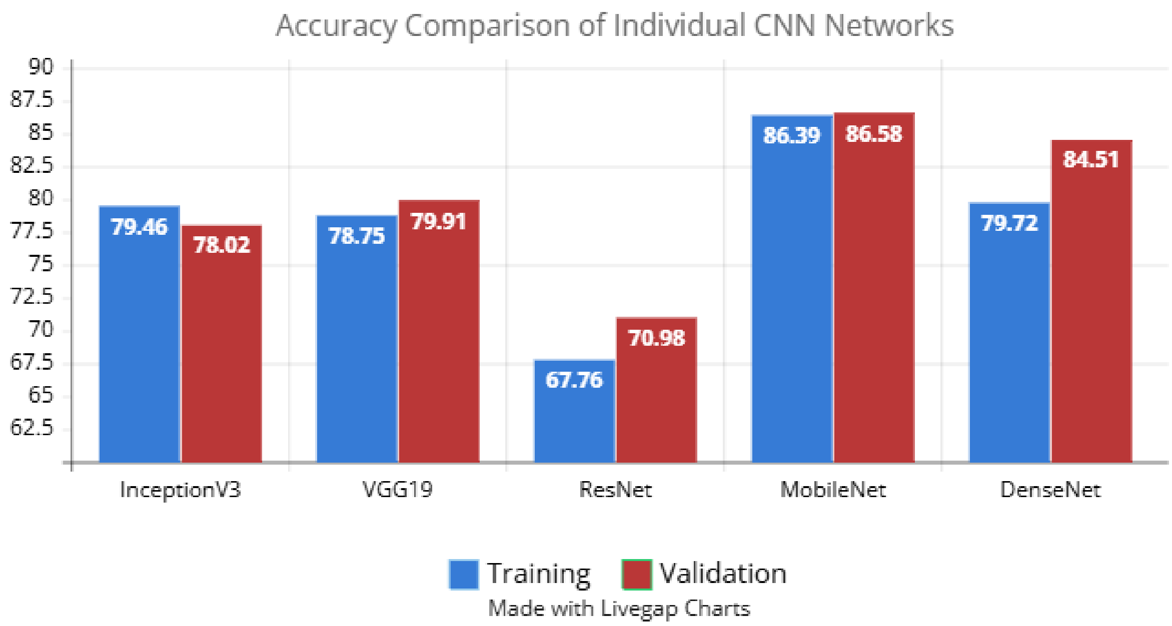

Figure 5.6: Accuracy comparison among individual CNN.

Using a wide range of datasets, this extensive study explores the effectiveness of deep convolutional neural networks (CNNs) in identifying and categorizing different cricket shots. By utilizing a dataset that includes many photographs of cricket shots, the study uses an advanced augmentation technique to improve the training data and guarantee strong model performance. The study investigates the effectiveness of original CNNs, transfer learning strategies, and ensemble models in the field of cricket shot categorization. Specifically, the study carefully examines the models' classification accuracy and computing efficiency, identifying them as essential components of the predictive pipeline.To categorize cricket shots, four well-known CNN-based models—InceptionV3, VGG19, MobileNet, DenseNet and ResNet—are put through a rigorous testing process. Remarkably, MobileNet stand out as the best models, with each model obtaining an impressive 86.58% model accuracy, as Table 5.1 shows. Although InceptionV3 exhibits a high 79.46% training accuracy, its slightly lower 78% model accuracy raises the possibility of an overfitting problem. MobileNet performs consistently on both training and validation datasets, with a balanced training accuracy of 86.39% and a model accuracy of 86.58%.

The study emphasizes how important augmentation techniques are for raising the accuracy and resilience of models. The work improves the training process by creating more images through augmentation approaches, which helps the models generalize better to unknown input.The paper does, however, clearly recognize the computational burden that comes with training deep CNN models, particularly when using ensemble methods. Future studies could investigate methods such as the snapshot ensemble to reduce the computing load while preserving high accuracy in order to address this.

A thorough examination shows that the use of segmentation methods prior to classification may improve the capacity of CNN models to extract relevant features, which may result in higher classification accuracy. This method emphasizes how crucial pre-processing stages are to deep learning models' overall efficacy in sports analytics.

The study also highlights how ensemble models may be better than individual CNN architectures. An ensemble can improve prediction performance by using the advantages of each architecture by merging multiple models.This observation is consistent with the larger deep learning trend that ensemble methods are becoming more and more valued for their capacity to increase robustness and accuracy.

5.4 Summary

Tthe research offers insightful information about the performance measures of several CNN architectures. It emphasizes how crucial it is to choose and optimize models carefully in order to get the greatest outcomes. The study's comprehensive accuracy measures are a vital resource for future investigations, adding to the current conversation about deep learning techniques optimization for computer vision and sports analytics.This work essentially provides a sophisticated investigation of CNN-based models for cricket shot classification, emphasizing the complex interactions across various architectures and augmentation techniques.The results highlight the significance of constant innovation and adjustment in the quickly developing field of deep learning, opening the door for further developments in sports analytics and other domains.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The study "Cricket Shots Classification using CNN" has ramifications that go beyond the boundaries of academics and have the potential to have a significant influence on both society and the sports sector. Sports analytics could be revolutionized by the accurate and automatic classification of cricket shots using cutting-edge AI algorithms. This could result in better player performance monitoring, more effective teaching methods, and more engaging viewing experiences.In the field of sports analytics, the research's societal impact is especially noticeable. With the use of Convolutional Neural Networks (CNNs), accurate and effective cricket shot classification will be possible. This research will enable analysts and coaches a comprehensive understanding of player tactics and strategies. This can make it easier to make data-driven decisions, which opens the door to more specialized training plans and strategic planning. Improved player performance analysis has the potential to result in.The incorporation of cutting-edge AI-driven analytics has the potential to completely transform the viewing experience for media and broadcasters. Real-time statistics, highlights, and insights during live matches can be made possible by automated shot classification, giving viewers a better comprehension and appreciation of the game. This increased interaction has the potential to increase viewership and fan devotion, which would benefit the sport's overall expansion.Furthermore, computerized cricket shot classification techniques have the potential to democratize sports analytics due to their price and accessibility. These developments can level the playing field and encourage greater involvement in cricket by helping grassroots and amateur cricket teams, who might not have access to sophisticated analytical tools. This supports international initiatives that encourage participation in sports from a variety of cultures and geographical areas by promoting inclusivity and accessibility.A layer of robustness is added by the research's emphasis on the practical use of CNN models and the comparative examination of multiple methodologies, guaranteeing that the solutions generated are not only efficient but also scalable and context-adaptable. This has the potential to expand the benefits of this research beyond cricket and advance sports technology overall by opening the door for the incorporation of AI-driven sports analytics into a variety of sports.

To sum up, the study of classifying cricket shots using CNNs has a great deal of potential to improve society by improving sports analytics' accuracy and depth, developing players, improving the viewing experience, and encouraging diversity in sports participation.

6.2 Impact on Environment

The research on "Cricket Shots Classification using CNN" is mostly concerned with sports analytics and technology developments, but it also has a subtle but significant environmental influence. Although the application of Convolutional Neural Networks (CNNs) to sports analytics has led to important advances in the analysis of player performance and fan interaction, it necessitates extensive computational procedures. Complex neural network training and optimization need a significant amount of processing power, frequently requiring energy-intensive hardware such as graphics processing units (GPUs).

The energy used to train and implement these sophisticated models has an effect on the environment. The high processing demands raise energy consumption and add to the carbon footprint, particularly in situations involving big datasets and complex model designs. This calls for consideration of the effects that cutting-edge sports analytics technologies will have on the environment.

It's crucial to understand that developments in cloud computing techniques, sustainable computing methods, and hardware efficiency are always changing. As the environmental risks associated with AI applications become more apparent to researchers and developers, efforts are being made to optimize hardware and algorithms for energy efficiency. The use of energy-efficient GPUs, code optimization to lower computational overhead, and the utilization of renewable energy sources are examples of green computing techniques that are becoming more and more popular.Additionally, using cloud-based platforms for model deployment and training can provide advantages for energy efficiency.Cloud service providers can lessen their overall environmental effect by utilizing renewable energy sources at scale and by having the capacity to install more energy-efficient cooling systems.

In summary, while research on CNN-based cricket shot classification has great potential to advance sports analytics, it is crucial to strike a balance between these developments and environmental sustainability. Through adoption of energy-efficient methodologies, enhancement of computing procedures, and utilization of renewable energy resources, the study can make a sustainable contribution to the field of artificial intelligence. This simultaneous emphasis on environmental stewardship and technological innovation guarantees that the advantages of cutting-edge AI applications can be realized without endangering the condition of our world.

6.3 Ethical Aspects

The entire technique of the study "Cricket Shots Classification using CNN" is based on ethical considerations. Using player data and video footage requires a strong commitment to maintaining confidentiality and privacy while abiding by legal and ethical requirements. A key component of ethical research is obtaining informed consent, which is carefully sought from the people whose data is being used in the study.

Making sure that the application of these cutting-edge AI techniques does not violate people's rights or result in abuse is vital, especially considering the possible influence of this research on sports analytics and the larger sports community. The proper management and anonymization of data to safeguard player identities and guarantee that data usage complies with established guidelines is part of the research's ethical component. It is crucial that the research process be transparent, with thorough documentation of methods, model structures, hyperparameters, and findings. This openness promotes confidence among stakeholders and among the research community in addition to facilitating scrutiny and repeatability. Proper knowledge distribution guarantees that scientific discoveries and technology developments are implemented morally and fairly in all tiers of sports, from amateur leagues to professional ranks. Additionally, consideration is given to the possible effects of AI-driven statistics on players' careers and public perception in the research process. A major ethical responsibility is making sure the analysis is impartial, fair, and considerate of the athletes' autonomy and privacy.

In conclusion, the study on CNN-based classification of cricket shots must take ethical issues into account. Through its emphasis on privacy, informed consent, transparency, and responsible use, the research demonstrates its dedication to maintaining ethical norms and promoting sports analytics as a profession. This commitment to moral rectitude guarantees that technology breakthroughs benefit both the sports industry and society at large.

6.4 Sustainability Plan

The "Cricket Shots Classification using CNN" research project's sustainability plan is painstakingly designed to reduce environmental effects while guaranteeing continued benefits to society and the sports sector. In order to lower the overall energy consumption related to model training and deployment, efforts will be focused on improving computational efficiency, implementing energy-efficient techniques, and investigating cloud computing options.

The application of algorithmic improvements that minimize computational overhead and the use of energy-efficient hardware, such as GPUs designed for lower power consumption, are important tactics. In order to reduce the research's carbon footprint, the team will make use of cloud-based systems that make use of renewable energy sources and sustainable infrastructure. Green data management and storage procedures will also be followed. In order to reduce storage requirements and energy consumption, this involves utilizing effective data storage solutions, applying data compression techniques, and routinely analyzing data to make sure only relevant information is maintained.

6.5 Summary

Constant awareness and incorporation of green computing principles are given top priority in the plan. The research team will integrate sustainable computing methods into their workflow and keep up to date on the most recent advancements in the field. This includes reviewing the sustainability strategy on a regular basis to make sure it stays up to date with emerging technologies and best practices.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Summary of the Study

The "Cricket Shots Classification using CNN" study is a thorough examination of the use of cutting-edge artificial intelligence methods in sports analytics. The project attempts to improve the accuracy and efficiency of cricket shot categorization by using deep Convolutional Neural Networks (CNNs) with a comprehensive dataset of cricket shot videos. The study carefully prepares and enhances the dataset to guarantee reliable and representative input for training and assessing the model.

The ability of six CNN-based models, including well-known architectures like ResNet, Inception, and VGG, to identify and categorize different cricket shots is put through a rigorous testing process.Through the process of fine-tuning pre-trained models for the particular objective of cricket shot categorization, the study investigates the potential of transfer learning and provides important new insights into the performance and generalization capacities of the models. The subtle differences in accuracy emphasize the value of data diversity and augmentation techniques, particularly when the input differs from the training set.

The study highlights how ensemble models may be more advantageous than individual ones. The project intends to improve classification robustness and accuracy by integrating different CNN models, offering coaches and analysts a more dependable analytical tool. A detailed analysis of how dataset size affects prediction powers is conducted, supporting suggestions for ongoing augmentation and updates to sustain and enhance model performance.The study is heavily reliant on ethical issues, with a particular focus on protecting player privacy and obtaining informed consent before using any video material. Code details, model architectures, hyperparameters, and results are all openly disclosed as part of the research process to promote responsible knowledge dissemination, scrutiny, and reproducibility.

The study outlines a sustainable strategy by acknowledging the effects that using energy-intensive AI technologies will have on the environment. To reduce energy consumption, this strategy calls for increasing computational efficiency, using energy-efficient algorithms, and utilizing cloud computing services. The utilization of renewable energy sources and the incorporation of green computing techniques demonstrate the research team's commitment to environmental sustainability.

All things considered, the study's findings provide a substantial contribution to the scholarly conversation about sports analytics and have real-world applications for improving player performance analysis, coaching techniques, and spectator experiences. In addition to advancing the field of AI-driven sports analytics, the project emphasizes environmental responsibility and ethical behavior. Through an in-depth examination of CNN-based cricket shot categorization, the research has significant potential to revolutionize sports analytics and enhance the fair and long-term use of cutting-edge technologies in athletics.

7.2 Conclusions

The study "Cricket Shots Classification using CNN" represents a significant development in the use of deep learning methods in the field of sports analytics. The effectiveness of many Convolutional Neural Networks (CNNs) for the job of cricket shot categorization has been comprehensively examined in this paper, including insightful information about model performance, transfer learning, and ensemble approaches.

The results of our analysis show that the accuracy and efficiency of cricket shot categorization are much improved by using pre-trained CNN models that have been adjusted for the particular task. When it comes to classification accuracy, the ensemble approach—which integrates the best features of several CNN architectures—consistently performed better than the individual models under evaluation. This illustrates how ensemble approaches have the potential to offer sports analytics professionals more trustworthy and durable analytical tools. The significance of data preprocessing and augmentation in enhancing model performance was also emphasized by the study. The models achieved greater accuracy and improved generalization by carefully prepping the dataset and using augmentation approaches. These results highlight how important diverse and high-quality data are when training successful deep learning models.

Our research technique included ethical concerns at every stage, with a particular focus on protecting player privacy and gaining informed consent before using any video material. The responsible and humane conduct of the research was guaranteed by the transparency of the documentation and the observance of ethical criteria.

Energy-intensive AI technology deployment's environmental effects were also considered, and a sustainability strategy was developed that calls for increasing computational efficiency, using energy-efficient algorithms, and utilizing cloud computing services. Our passion to undertake research that not only enhances technological innovation but also corresponds with ecological sustainability is shown in our commitment to environmental responsibility.

As a result, this study offers a thorough assessment of CNN-based cricket shot classification and offers useful recommendations for improving player performance analysis, teaching techniques, and spectator experiences. The knowledge gathered from this study opens up new avenues for future research and growth in the field of sports analytics. This study establishes a standard for the responsible and significant deployment of deep learning by fusing cutting-edge AI technology with moral and sustainable behavior.

7.3 Implication for Further Study

The results of this study, which classified cricket shots using convolutional neural networks (CNN), provide insightful information and open up new avenues for sports analytics research. A noteworthy recommendation for future research is to investigate different image-processing techniques, like motion analysis and contrast augmentation, to deal with cases of incorrect classifications found in the existing models. These methods might increase the algorithms' capacity to recognize minute variations among different cricket shots, which would raise classification accuracy.

Furthermore, including sophisticated preprocessing and data augmentation methods is proposed as a possible improvement for CNN models in feature extraction. Future studies could look into the use of transfer learning, domain adaptation, and synthetic data generation to improve model performance even further, especially when working with different datasets. Future research could examine the implementation of strategies like snapshot ensemble or model pruning to lessen the strain on computational resources given the computational intensity of the suggested ensemble approach. This suggests the need for more effective and scalable ensemble approaches in order to improve or preserve accuracy without sacrificing computing effectiveness. For real-world applications, research into maximizing the trade-off between computing cost and model performance will be essential.

Although the classification of cricket shots was the main emphasis of this study, there is a need to broaden the research's scope to include other sports and activities. In order to contribute to a more thorough knowledge of AI's function in sports, future research might go deeper into sports analytics approaches, possibly investigating unique architectures, different datasets, and real-world applications. Furthermore, incorporating contextual data into the classification models—such as player biomechanics and game context—may yield a more thorough study and precise predictions. This multifaceted strategy may greatly improve the use of AI in sports analytics by providing athletes, coaches, and analysts with richer insights.

To summarize, the research implications for future work include optimizing image-processing tactics, investigating effective group methods, and broadening the range of sports analytics studies. Future research in these areas can contribute to the field of sports analytics by advancing the use of AI technology in performance analysis, strategic planning, and the general knowledge of athletic activities.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:

CRICKET SHOTS CLASSIFICATION USING CNN: AN ENSEMBLE OF DEEP LEARNING MODELS FOR ACCURATE SHOT IDENTIFICATION

Student ID: [201-15-13784, 201-15-13943]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **cricket shots classification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**

CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, and CO3	Our project involves designing and implementing data processing that requires knowledge of fundamental engineering in data structure, algorithms. The project focuses on deep learning techniques, Model architecture which involves our computer	**Page no:** [26-30] **Section:** [3.2] **Page no:**

				architecture organization covering **K3 and K4.**	[1-7] **Section:** [1.1]
				The project management, Risk management, data privacy and security different components are system design covers our **K5 and K6.**	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33] **Section:** [3.4]
				Research methods and techniques lud included literature review and nental desin design covers **3.**	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	In our project Regulatory Compliance, data scope limitations, legal consultation, ethical consideration representatives EP2 Range of conflicting requirements the project navigates the challenge.	**Page no:** [23-24] **Section:** [2.4, 2.5]

3.	**EP3: Depth of analysis required**	Yes	CO2	Abundance and diversity of cricket shots, algorithms selection complexity, data analysis, algorithm evaluation and comparison, informed decision making, optimized solution are EP3 depth of analysis required for the projects and ensuring the chosen solution is well-suited to handle the complexities and challenges inherent data analysis.	**Page no:** [16-27] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO3	Complexity of cricket shot classification, player movements, match condition, shot technique, shot types, gameplay scenario, without specialized domain knowledge is more difficult to obtain the suited result.	**Page no:** [16-24] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	Yes	CO3	We have met to provide domain expertise, player performance assessment and coaching strategies. We also work for technology providers, supply tools, frameworks and deploy the classification system like scalability, reliability, efficiency of different types of cricket shots.	

6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	The choice of training data, model architecture and hyperparameters in cricket shots accurately. Model training and evaluation, stakeholder feedback and iterative development of those sites is our ultimate priority.	N/A
7.	**EP7: Interdependence**	Yes	CO4	We have meticulously outlined a financial plan to evaluate and the costs of our Final Year Design Project (FYDP)	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our initiative makes use of multiple resources to promote methodical study and further the development of CNN-based cricket shot categorization. These resources include state-of-the-art deep learning frameworks like TensorFlow and PyTorch, high-	**Page no:** [33-35] **Section:** [3.5]

				performance computing infrastructure, GPUs for accelerated processing, carefully selected annotated datasets of cricket shot photos, and stringent ethical considerations. These components are essential to our attempts to improve cricket shot recognition efficiency and accuracy using cutting-edge machine learning approaches.	
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	No		N/A	**Page no:** [24-31] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	No		N/A	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	By combining efficient project management with financial monitoring, this project tackles CO4 by guaranteeing careful planning, resource allocation, and budget estimation for the best possible resource utilization throughout the study lifetime. .	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	By putting patient privacy first, getting informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the moral application of cutting-edge healthcare technologies that abide by CO9.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	N/A	**Page no:** [26-34, 30-37] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

Sumit Mojumder_CLASSIFICATION OF CRICKET SHOTS USING CONVOLUTIONAL NEURAL NETWORK_V2

ORIGINALITY REPORT

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