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Identify Sports Activity from Video using LSTM

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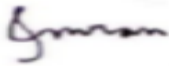
This Project report has been submitted in fulfillment of the requirements for the Degree of
Bachelor of Science in Software Engineering.

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APPROVAL

This thesis titled “Identify Sports Activity from Video using LSTM”, submitted by Sajidur Rahman, ID:171-35-1831 to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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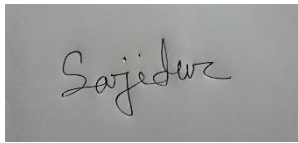


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Declaration

It hereby declares that this thesis has been done by me or us under the supervision of Mr. Md. Anwar Hossen, Lecturer (Senior Scale), Department of Software Engineering, Daffodil International University. It also declared that neither this thesis nor any part of this has been submitted elsewhere for the award of any degree.



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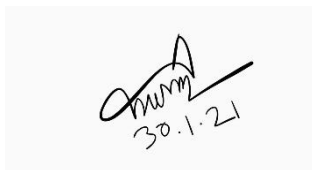
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TABLE OF CONTANT

APPROVAL	i
Declaration.....	ii
ACKNOWLEDGEMENT	iii
TABLE OF CONTANT	iv
LIST OF FIGURES	vi
LIST OF TABLES.....	vii
ABSTRACT.....	viii
CHAPTER 1	1
INTRODUCTION	1
1.1 Background:.....	1
1.2 Motivation of the Research:.....	1
1.3 Problem Statement.....	2
1.4 Research Questions.....	2
1.5 Research Objectives.....	2
1.6 Research Scope	2
CHAPTER 2	3
Literature Review.....	3
CHAPTER 3	4
Methodology.....	4
3.1 Proposed Model	4
3.2 Workflow	5
3.3 Data Collection	6
3.4 Data Pre-Processing	7
3.4.1 Video to Frame	7
3.4.2 Data Augmentation	8
3.5 Label Encoding	9
3.6 Features Extraction	9
3.6.1 Convolutional Neural Network (CNN).....	11
3.6.2 VGG16.....	12
3.7 Sequence Learning.....	12
3.7.1 Recurrent Neural Networks (RNN)	14

3.7.2 LONG SHORT-TERM MEMORY (LSTM).....	14
3.6 Evaluate Model Performance.....	15
3.6.1 Optimizer	15
Stochastic Gradient Descent	15
3.6.2 Loss Function.....	16
Categorical Cross-Entropy	16
CHAPTER 4	17
RESULTS AND DISCUSSION	17
4.1 Feature Extraction:.....	17
4.2 Sequence Learning.....	19
4.3 Prediction	21
CHAPTER 5	23
CONCLUSION AND FUTURE WORK	23
5.1 Findings and Contributions.....	23
5.2 Conclusion	23
REFERENCES	24
Appendix -A.....	25
List of Abbreviation.....	25
Appendix –B	26
Plagiarism Report.....	26

LIST OF FIGURES

Figure 3. 1 Proposed Model.....	4
Figure 3. 2 Prototype of our system.....	5
Figure 3. 3 Proposed model workflow.....	5
Figure 3. 4 Data set.....	6
Figure 3. 5 Frames of a video.....	7
Figure 3. 6 Data Augmentation.....	8
Figure 3. 7 Model Used for Extracting Feature.....	10
Figure 3. 8 Basic CNN Model.....	11
Figure 3. 9 VGG16 Model.....	12
Figure 3. 10 Model Used for Sequence Learning.....	13
Figure 3. 11 Basic RNN Model.....	14
Figure 3. 12 LSTM Model.....	15
Figure 3. 13 Gradient Descent.....	16
Figure 3. 14 Stochastic Gradient Descent.....	16
Figure 3. 15 Categorical Cross Entropy.....	16
Figure 4. 1 Train and Validation accuracy on CNN Model.....	18
Figure 4. 2 Train and Validation loss on CNN Model.....	18
Figure 4. 3 learning Rate of CNN Model.....	19
Figure 4. 4 Train and Validation Accuracy on LSTM Model.....	20
Figure 4. 5 Train and Validation Loss on LSTM Model.....	20
Figure 4. 6 learning rate of LSTM model.....	21
Figure 4. 7 Prediction 1.....	21
Figure 4. 8 Prediction 2.....	22

LIST OF TABLES

Table 4. 1 VGG16 Model Result	17
Table 4. 2 LSTM Model Result	19

ABSTRACT

Identifying human activity or action is difficult for any autonomous system. But the application of human activity recognition system is limitless. Like, an assistive robot can help people by identifying human activity. But identifying human activity is not easy task so in this work we tried to detect human activity more accurately with combination of CNN and LSTM deep learning algorithms with a large human activity dataset. In this work we first extract feature using CNN algorithm then we will use those features to train a LSTM model for sequence learning.

Keywords: Human Activity Recognition, Convolutional Neural Network, Recurrent Neural Network

CHAPTER 1

INTRODUCTION

1.1 Background:

The necessity of recognizing human activities is increasing limitless now a day. Human are constantly interacting with the things around him/her those interaction is human activity which is very difficult for any system. Recognition of human activity plays an important role in communication between human beings and intelligence system. If a system can recognize human activity, then it's also can react with human. For example, a self-driving car can avoid accident if it sees a person is crossing road so it will stop. We can also implement Human activity recognition in health care, elderly health monitoring, day care center, rehabilitation center, human computer interaction, security surveillance etc. Actually, the implementation is of human activity recognition is limitless. For this we need to recognize human activity with good accuracy unless it can cause lot of problem instant of helping or decreasing our work. So, many researches are going on to detect human activity but still it is a most common problem from any intelligent system. To gain the better performance in human activity recognition with less computation power or cost is a become a major challenge.

1.2 Motivation of the Research:

Detecting human activity can brings new application for intelligence system. The application of this type of system will be limit less. Like autonomous vehicles can use this system for taking decisions Assistive robot must need this type of system assistive robot can decrease out work. We can build smart city where robots are also interacting with us. But understanding human activity critical for any intelligent system with better performance using low computational power. Now a days the computational power needed for system like human

activity recognition system is not rare anymore and huge number of data can be found publicly thanks to easy access to internet and video sharing platform. So Those application computational power and dataset availability motive me to research on Human Activity Recognition.

1.3 Problem Statement

Identifying human actions from still image is easier than video. But application of human action detection from video has more application than still image. But it is very difficult to detect. Intelligent system takes input continuously if the input is from a camera then it is a video. So, identifying activity is a hard task for this type of system.

1.4 Research Questions

- How accurately deep learning model can detect human activity from video data?

1.5 Research Objectives

- To recognize human activity recognition from video.
- To get better accuracy using combination of multiple deep learning algorithms

1.6 Research Scope

The Scope area of this research is under the **Kinetics 700** dataset. In this work, we focus on understanding actions using only their visual content. Right Now, people are attracting by automation. For automation, automation system needs to interact with human in most of the cases. So, understanding human activity become a huge research area.

CHAPTER 2

Literature Review

Actor-Context-Actor Relation Network for Spatio-Temporal Action Localization (Junting Pan, Siyu Chen, Zheng Shou, Jing Shao , Hongsheng Li-2019) They work on three task here human action recognition, Spatio-Temporal Action Localization and Relational Reasoning using 2D-CNN and 3D-CNN. ADVERSARIAL VIDEO GENERATION ON COMPLEX DATASETS (Aidan Clark, Jeff Donahue, Karen Simonyan-2019) They use Generative model to generate natural images with dual video discriminator GAN model which they proposed. Understanding Human Actions in Video (Jonathan Stroud-2020) This paper introduced four novel techniques for performing action recognition (detailed 3d networks, motion learning from rgb videos, temporal hourglass networks, Compositional Temporal Grounding). Multi-Label Activity Recognition using Activity-specific Features (YanyiZhang, Xinyu Li, Ivan Marsic-2019) They introduced an artificial neural network that focuses on multi-label activity recognition. THREE BRANCHES: DETECTING ACTIONS WITH RICHER FEATURES (Jin Xia,f Jiajun Tang-2019) In this paper they show a way how to get richer information of global video clip, short human attention and long-term human activity.

CHAPTER 3

Methodology

3.1 Proposed Model

To detect human activity from video we will use combination of multiple deep learning model. For this work we use CNN and LSTM model show in figure 3.1. Since we have video which is sequence of frames so if we used only CNN then we may face some problem. For example, images of 2 videos one is closing door and one is opening door are almost same, so it will not give accurate result. So, we decided to use LSTM model to learn sequence from images or frames of a video. At the end our model is a combination of CNN and LSTM model where CNN will extract features from every frames of a video then that extracted feature for sequence learning which will able to describe the sequence of frames.

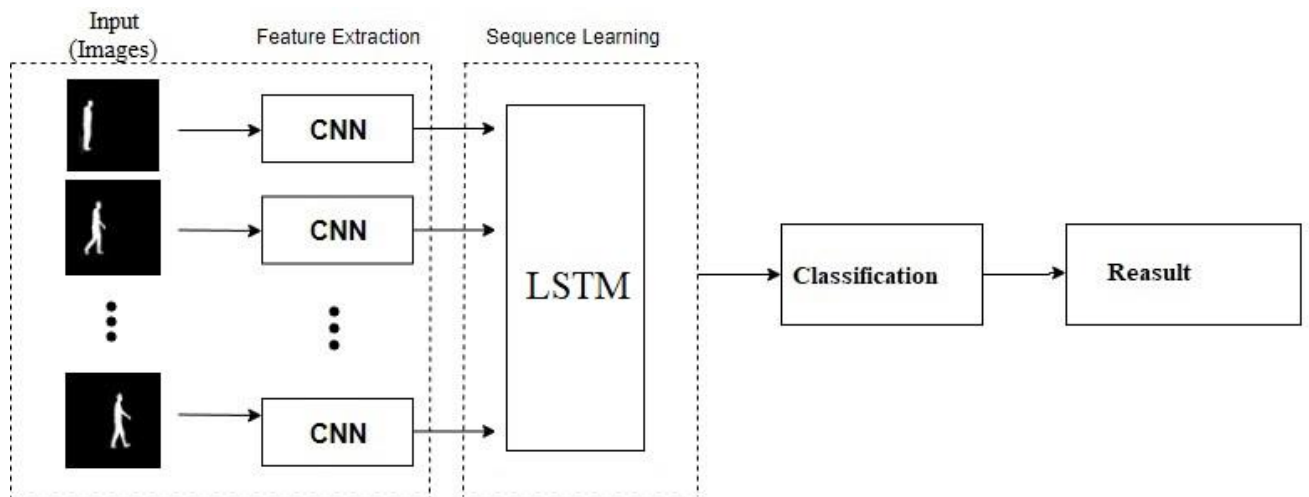


Figure 3. 1 Proposed Model

Figure 3.2 show the prototype for our system. We decide to make a font end for our system so that end user can visualize what we are trying to do in this work.



Figure 3. 2 Prototype of our system

3.2 Workflow

We used several steps start with collection raw data and end with predicting new data high accuracy. Figure 3.3 shows the workflow for our work.

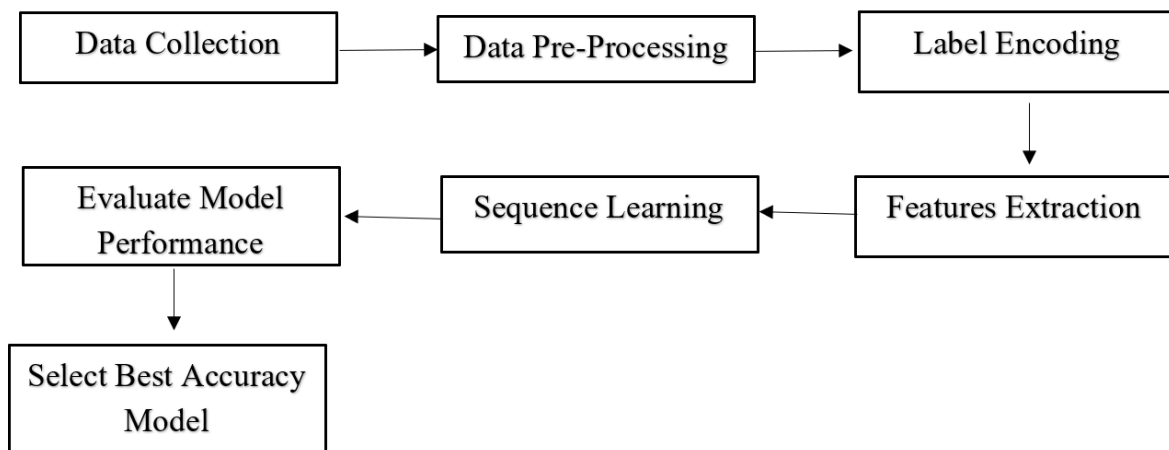


Figure 3. 3 Proposed model workflow

3.3 Data Collection

In this work we used a large data set of human activity (Kinetics 700) having URL of up to 650,000 videos covering 700 human action and each video has at least 10 seconds to perform the specific human action. For our work we collect video data for 5 classes (Due to hardware limitation).

```
print(badminton.head())
print(volleyball.head())
print(polo.head())
print(tennis.head())
print(icehockey.head())
```

		youtube_id	time_start	time_end	split
label					
playing	badminton	-43pzCFD0ms	0	10	train
playing	badminton	-5-94WML4hE	25	35	train
playing	badminton	-9oeVZ1AF8s	1	11	train
playing	badminton	-H0AfD0erfo	213	223	train
playing	badminton	-MUoF3Hs8QY	34	44	train
		youtube_id	time_start	time_end	split
label					
playing	volleyball	-20sSnusEso	0	10	train
playing	volleyball	-4C3x47i08U	8	18	train
playing	volleyball	-76uJz2GUZE	1	11	train
playing	volleyball	-9MFYKsDT_s	11	21	train
playing	volleyball	-IKInag2cxw	7	17	train
		youtube_id	time_start	time_end	split
label					
playing	polo	-1L06tE9vL0	40	50	train
playing	polo	-8pD5cFwVHo	0	10	train
playing	polo	-Zt0Sk9vBK8	93	103	train
playing	polo	-kya6WV0w9C	50	60	train
playing	polo	-ousyuJR8Dk	2	12	train
		youtube_id	time_start	time_end	split
label					
playing	tennis	--56QUhyDQM	185	195	train
playing	tennis	-2egBNANLTg	9	19	train
playing	tennis	-AXdgnbvdKU	24	34	train
playing	tennis	-O4W3NAS-uA	150	160	train
playing	tennis	-OcwiIcSIP8	9	19	train
		youtube_id	time_start	time_end	split
label					
playing	ice hockey	-2gHxh_3BDc	0	10	train
playing	ice hockey	-6i6pP8ImR4	18	28	train
playing	ice hockey	-7U4xK7h6YM	16	26	train
playing	ice hockey	-CDg6j0siZE	38	48	train
playing	ice hockey	-FMHcSxVM3c	13	23	train

Figure 3. 4 Data set

3.4 Data Pre-Processing

3.4.1 Video to Frame

Since we will use CNN model, so we need image data not video data. We know that video is combination of frames or images with times. So multiple images can represent a video. Since we have video data, so we will process our video to image in 10 frames while performing that specific task in that video. We also remove those data not having 10 frames. Because that can create problem while we will train LSTM model for sequence learning. So, our data must be in a constant sequence while we will train our model. Otherwise it will show wrong answer when will predict class of a new video. Figure 3.5 show 10 frames of a video when that specific human activity is performing.

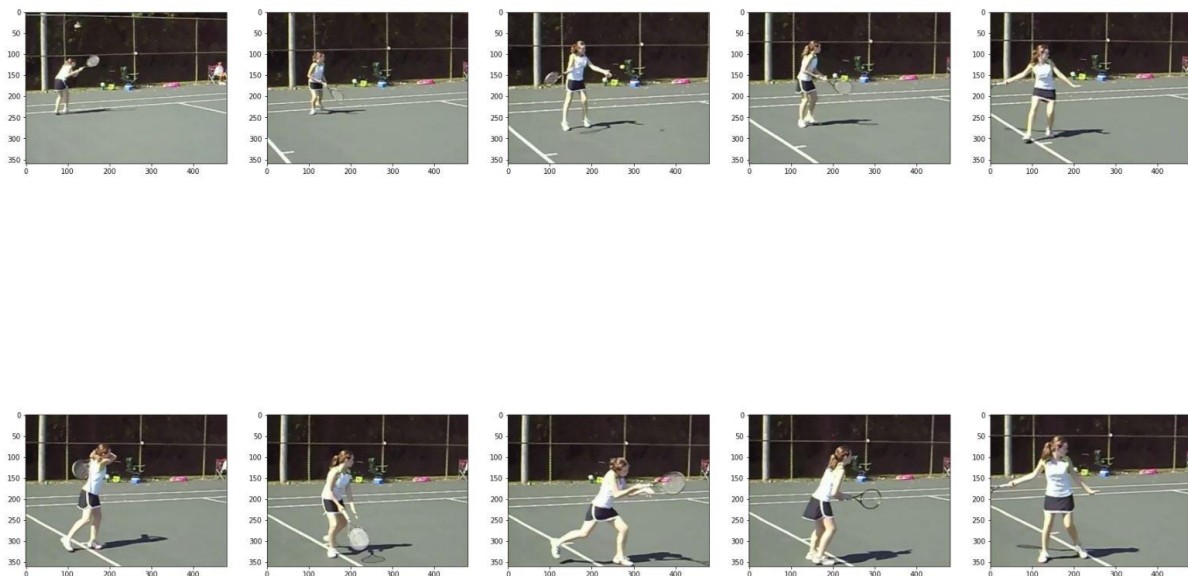


Figure 3. 5 Frames of a video

3.4.2 Data Augmentation

Data augmentation techniques to create varieties of image from same image. Its help to create more efficient model. For example, a human activity can be capture from different angel also in different zooming. So, data augmentation can be done using zooming, changing brightness, changing rotation, doing vertical or horizontal flip etc. So, we also use those techniques to improve our work. Figure 3.6 show how data augmentation looks like.It is a representation of same image.

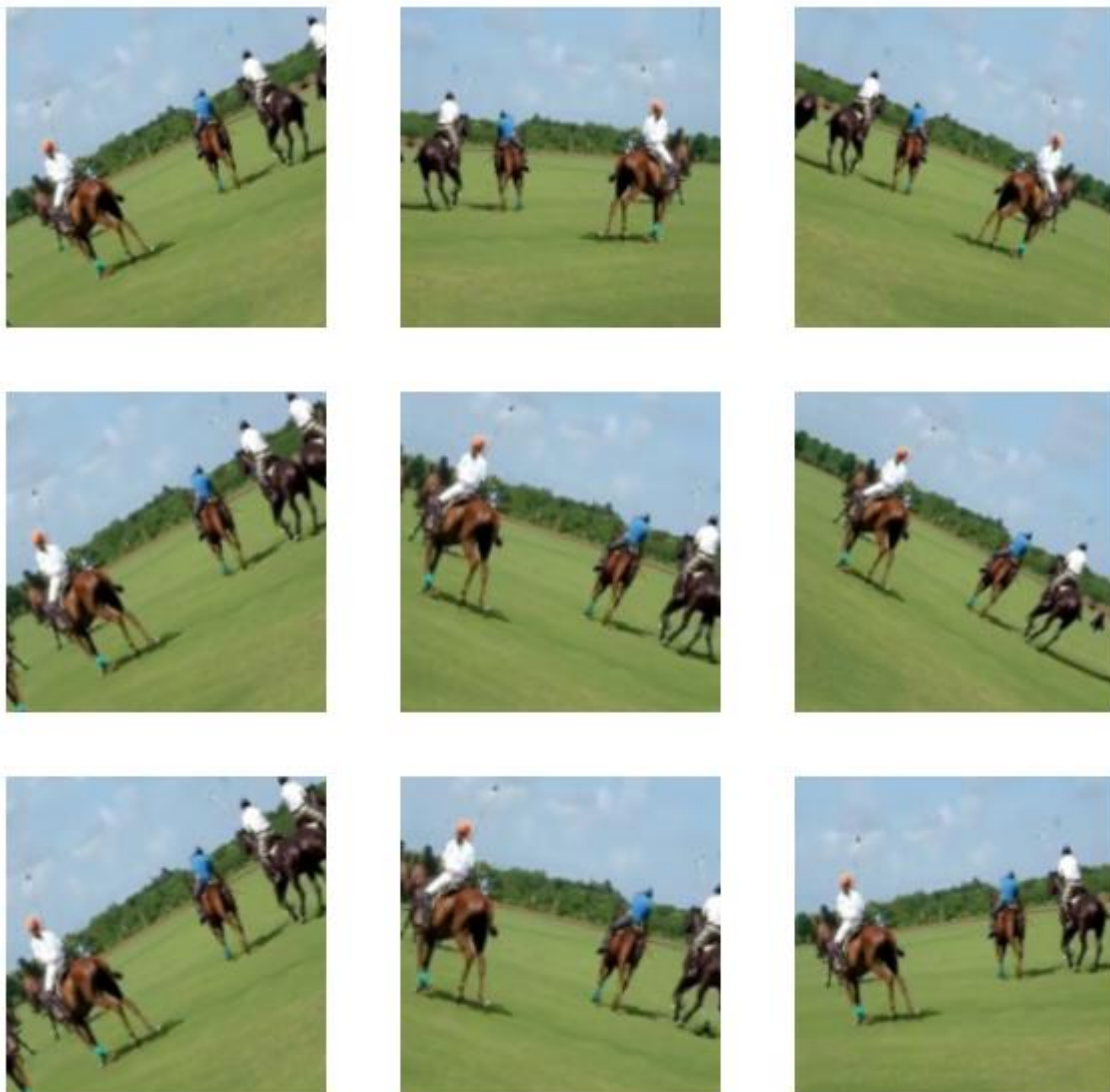


Figure 3. 6 Data Augmentation

3.5 Label Encoding

So here have five class of data playing badminton, playing polo, playing volleyball, playing tennis, playing ice-hockey. So, we use label encoding to convert that labels in machine readable form so that our loss function easily deals with probability of each label. Now our labels become

Label	Encoded Label
Playing Badminton	0
Playing Ice hockey	1
Playing Polo	2
Playing Tennis	3
Playing Volleyball	4

3.6 Features Extraction

Feature Extraction is the process of dimensionality reduction. We have 10(here every video duration is 10 second while performing that specific activity) images for every video so it is huge for computing and learn sequence so we will extract important information or features from every image. For Extracting feature, we will use Vgg16 CNN model. We will cut the maxpooling layer before dense layer. Cause we don't need to classify images we only need feature from the images. More details can be found at Section 3.6.1 and 3.6.2 where we discuss more about CNN and VGG16 Model. Figure 3.7 shows the model we used in our work to extract feature from images.

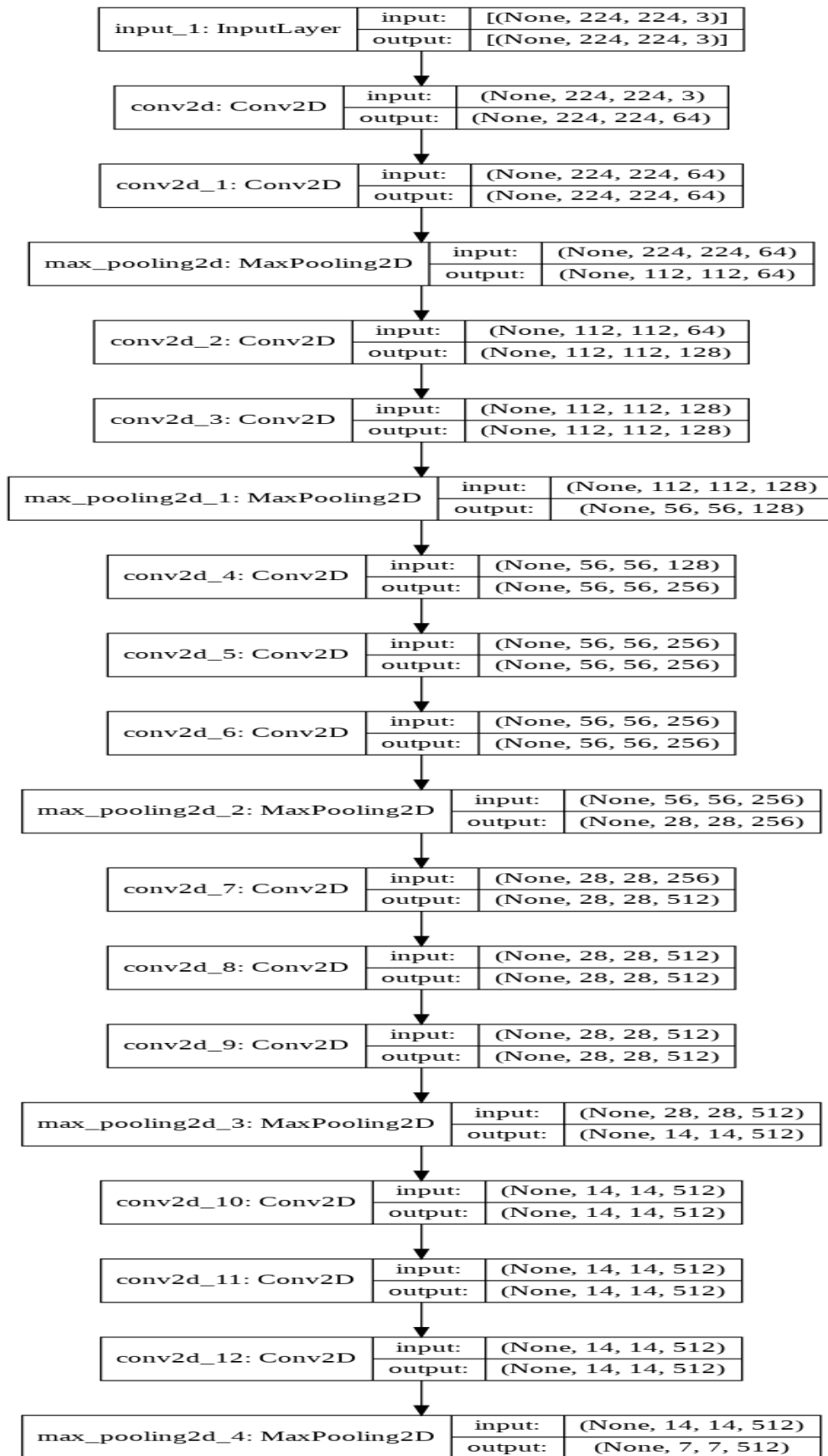


Figure 3. 7 Model Used for Extracting Feature

3.6.1 Convolutional Neural Network (CNN)

Convolutional neural network is a deep learning architecture developed based on how living creatures see anything. This architecture like ordinary neural networks because it has weights and biases like ordinary neural networks. It starts with input layer and end with output layer and having multiple hidden layers. Hidden layers are for multiple combination of convolutional layer and pooling layer for extracting features of an image then it connects with fully connected layer for classification. But there are many CNN architectures available one of them is Vgg16 which gained recognition for achieving good results. Figure 3.8 is visual representation of a CNN Model.

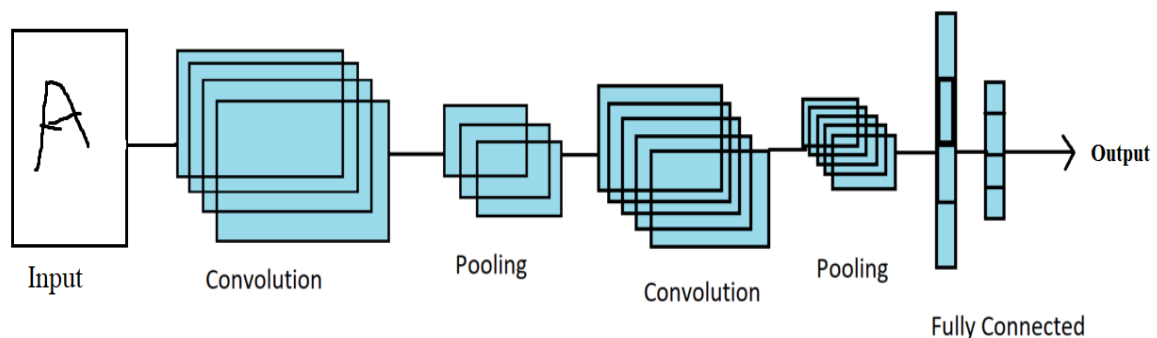


Figure 3. 8 Basic CNN Model

3.6.2 VGG16

Vgg16 is a convolution neural network which win ILSVR competition in 2014 with is proposed by K. Simonyan and A Zisserman. Till now it is one of the best architectures. Unlike other architecture it always uses 3x3 filter with stride 1 in convolution layer and in pooling layer it uses 2x2 filter of stride 2. The 16 in VGG16 mean 16 layers of convolution layer and pooling layer. At end it also has 3 fully connected layers. Figure 3.9 show all layers of a VGG16 Model

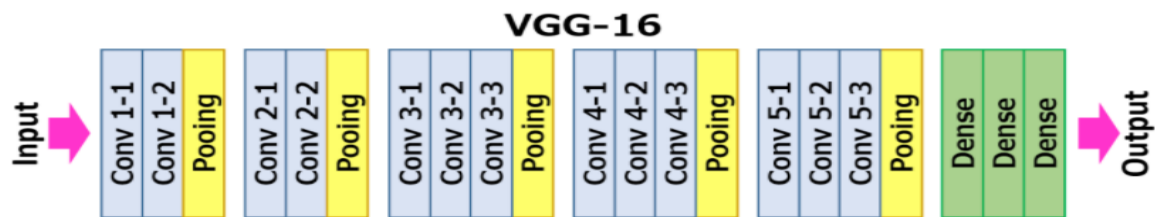


Figure 3. 9 VGG16 Model

3.7 Sequence Learning

Multiple frames or images representation of a video which describe visual difference with respect to time. So, an activity can be also representing a sequence of visual difference with times. So, we extract feature from frames which represent our video data. Since we have feature of every image now, we need to learn the sequence so that we can identify every human activity with high accuracy. For sequence learning we will use an RNN based model LSTM. We use basic LSTM model which learn sequence from extracted features and classify 5 different class. (Since we are using 5 types of human activity to train our model for hardware limitation). In Figure 3.10 we can see all layers we used for a LSTM model for learning sequence.

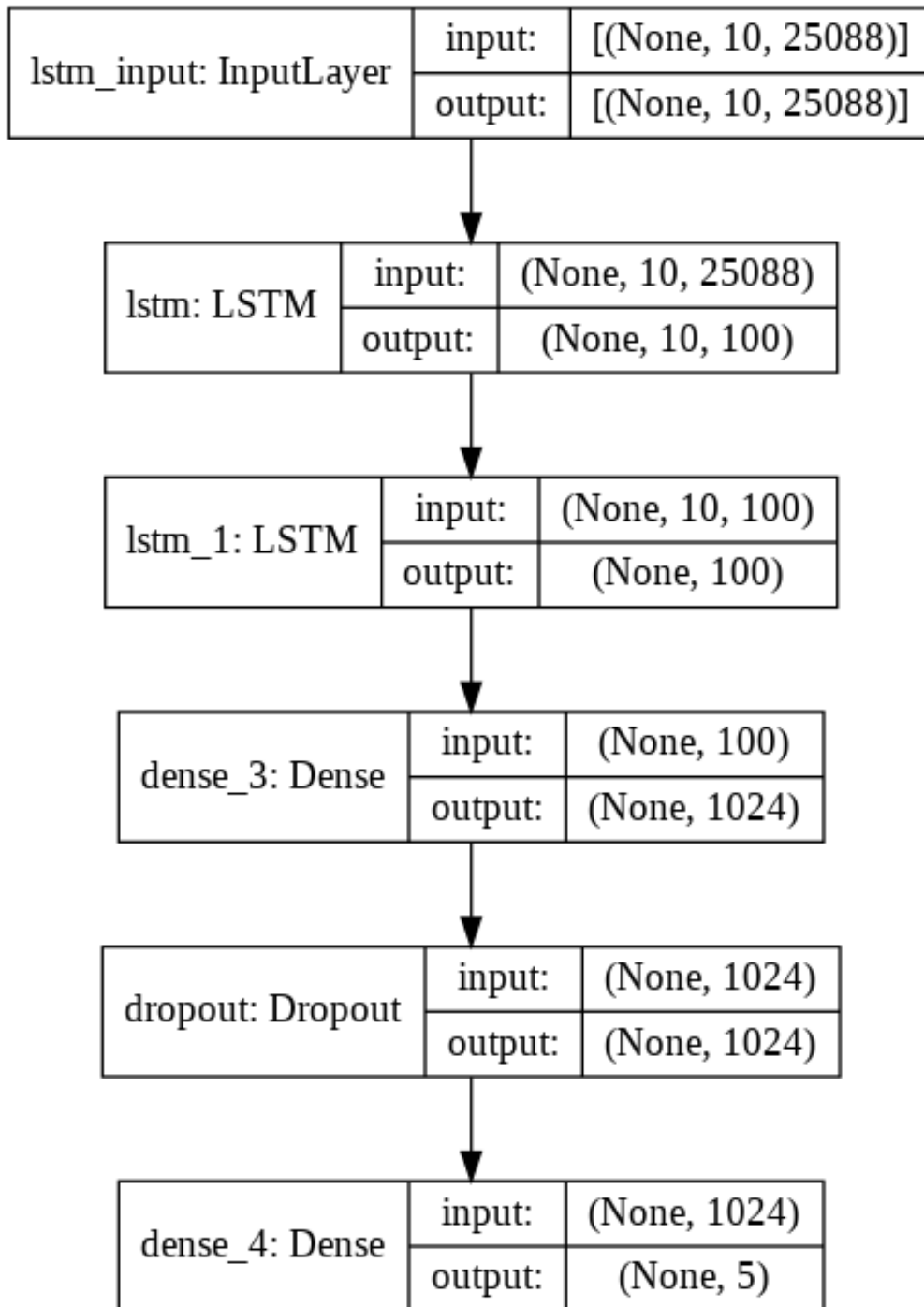


Figure 3. 10 Model Used for Sequence Learning

3.7.1 Recurrent Neural Networks (RNN)

It is also a deep learning algorithm. It is the first deep learning algorithm having state. So, it is used for sequence data. Having an internal memory in this algorithm it can remember many things about its input which makes this algorithm to solve sequence-based problems. This algorithm is used to solve data series data, audio, video, weather, speech etc.

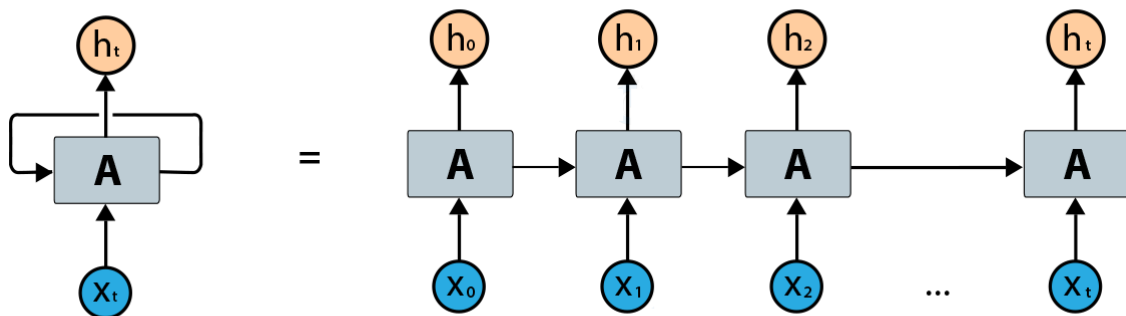


Figure 3.11 Basic RNN Model

3.7.2 LONG SHORT-TERM MEMORY (LSTM)

Long short-term memory networks are an evolved form of RNN algorithm. LSTM can remember inputs over a long period of time. This algorithm can perform operations like a computer does to its memory. It can read, write, delete data from its internal memory. LSTM has three gates: input gate, forget gate, and output gate. The input gate deals with input data, whether or not to let it in; the forget gate deletes data when it is not important; the output gate deals with timesteps.

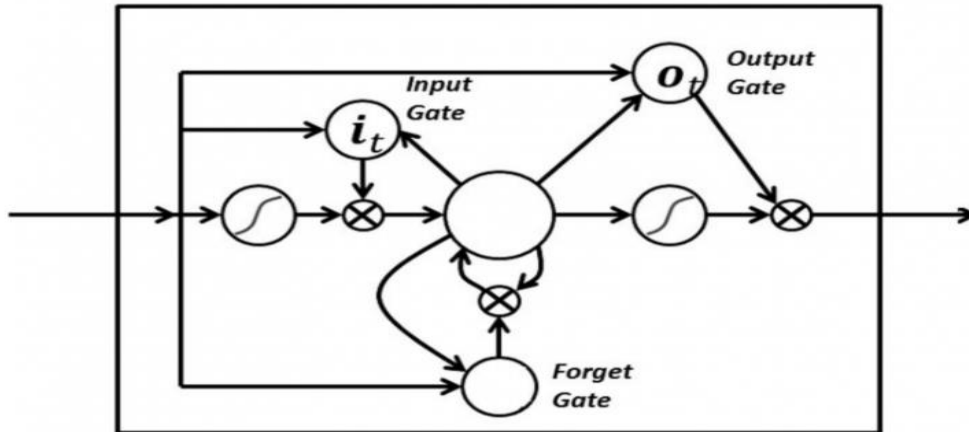


Figure 3. 12 LSTM Model

3.6 Evaluate Model Performance

We evaluate both model by using best parameter in Optimizer and selecting best loss function which gives the best accuracy for identifying activities.

3.6.1 Optimizer

Stochastic Gradient Descent

The slope of a function is called gradient. So gradient descent means descending a slope to reach the lowest point on the surface. Gradient descent calculates gradient of full data set for each iteration. It useful for getting less noisy minima. But the problem is when talking about large dataset like millions of samples it need lots of calculation which makes it slow. To overcome this problem stochastic gradient descent, use a random sample to perform each iteration. The path to reach the minima is noisy but we can reach that minima with a very short training time than gradient descent. One more thing for noisy path its SGD took high number of iteration but still the computational power is less than normal gradient descent.

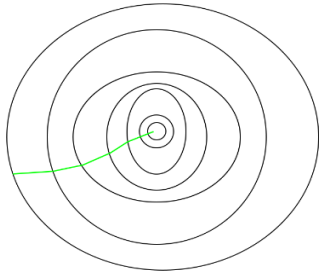


Figure 3. 14 Gradient Descent

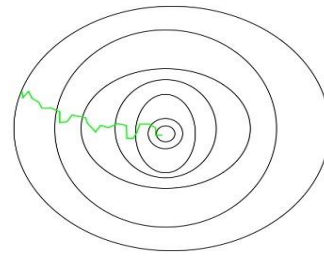


Figure 3. 13 Stochastic Gradient Descent

3.6.2 Loss Function

Categorical Cross-Entropy

When we have a problem like each sample belongs to one n classes, we usually want the probability over n classes. For this categorical cross-entropy loss is perfect since it is a combination of softmax activation and cross entropy loss. Using this loss function, we will get probability of each classes for an input.

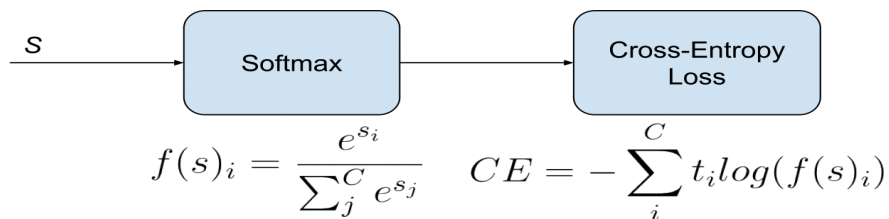


Figure 3. 15 Categorical Cross Entropy

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Feature Extraction:

We extract Feature from 20000 images with vgg16 model which gives 66% accuracy while testing and 49% accuracy at the time of validation. We tried with different learning rate but using high learning rate the loss is very high and low learning rate it takes lots of time. So, we start learning rate at 0.1 and reduce the learning rate in every 10 epochs so it can receive local minima with less time. So, at epoch 50 the learning rate reduced to 0.003125 which gives 66% accuracy while training and for validation 45%.

Epochs	Learning Rate	Training Accuracy	Validation Accuracy
1~8	0.1	22%	20%
9~18	0.05	22%	21%
19~27	0.025	21%	20%
28~37	0.0125	25%	30%
38~48	0.00625	51%	41%
49~50	0.003125	66%	45%

Table 4. 1 VGG16 Model Result

In figure 4.1 and 4.2 we can see the train and validation Accuracy as well as Train and Validation losses while we train CNN Model So that we can extract feature from it.

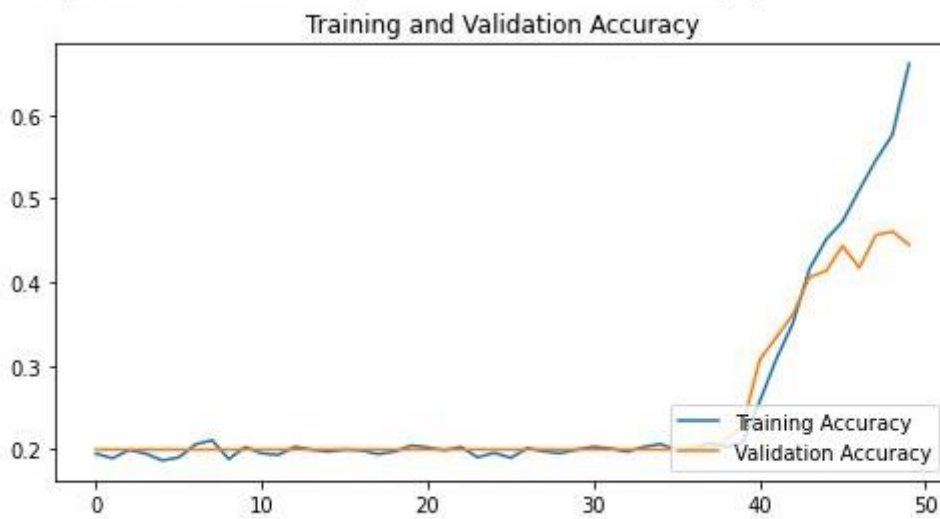


Figure 4. 1 Train and Validation accuracy on CNN Model

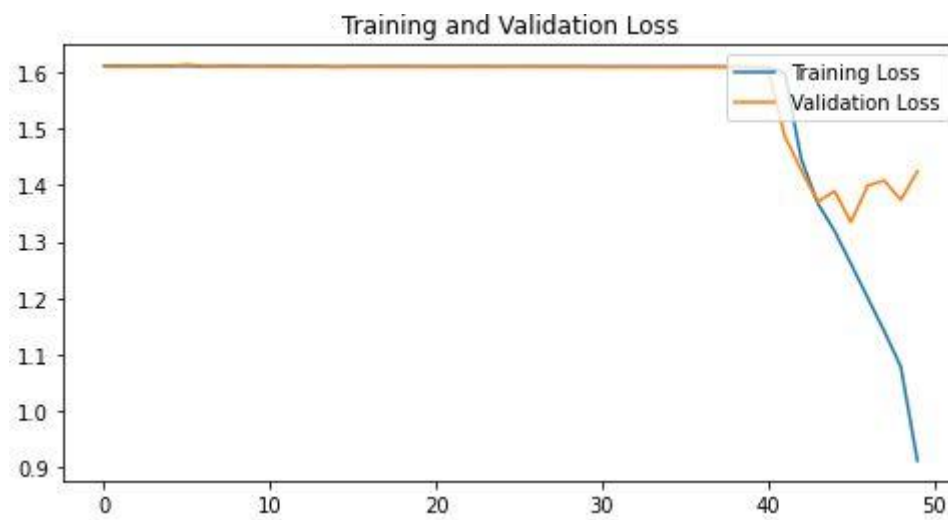


Figure 4. 2 Train and Validation loss on CNN Model

Learning rate reduce using step decay method with epoch drop at 10.0 and initial learning rate is 0.1 figure 4.3 show learning rate changes with epochs.

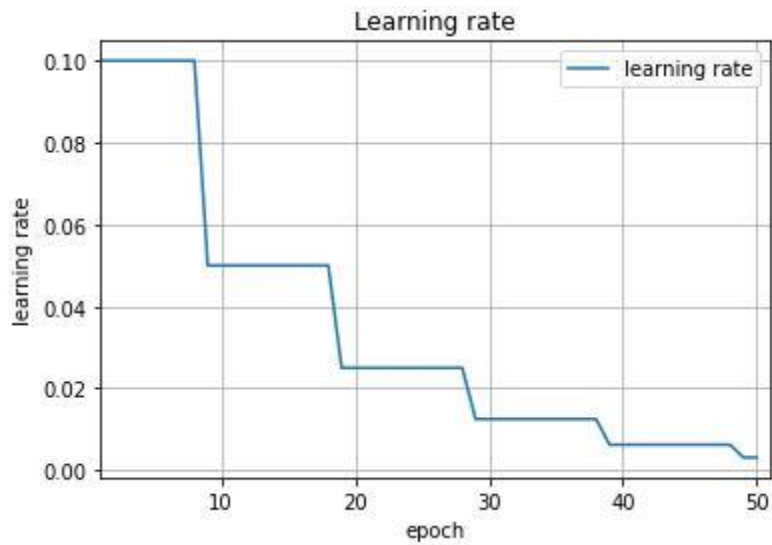


Figure 4. 3 learning Rate of CNN Model

4.2 Sequence Learning

After extracting feature, we use those extracted features to learn sequence. So, using an LSTM model with extracted featured we got a good result of 88% with 20 epochs. We used same learning rate reduce technique to reach local minima, but we change learning rate in every 10 epochs which gives use the result below.

Epochs	Learning Rate	Training Accuracy	Validation Accuracy
1~8	0.1	68%	44%
9~18	0.05	85%	46%
19~28	0.025	96%	50%
29~30	0.0125	99%	53%

Table 4. 2 LSTM Model Result

In Figure 4.4 we have Accuracy of train and validation with respect of epochs. In Figure 4.5 we can visualize loss of train and validation with respect of epoch while on LSTM model. We can also see the learning rate of LSTM model which is decreased using step decay method at Figure 4.6 below.

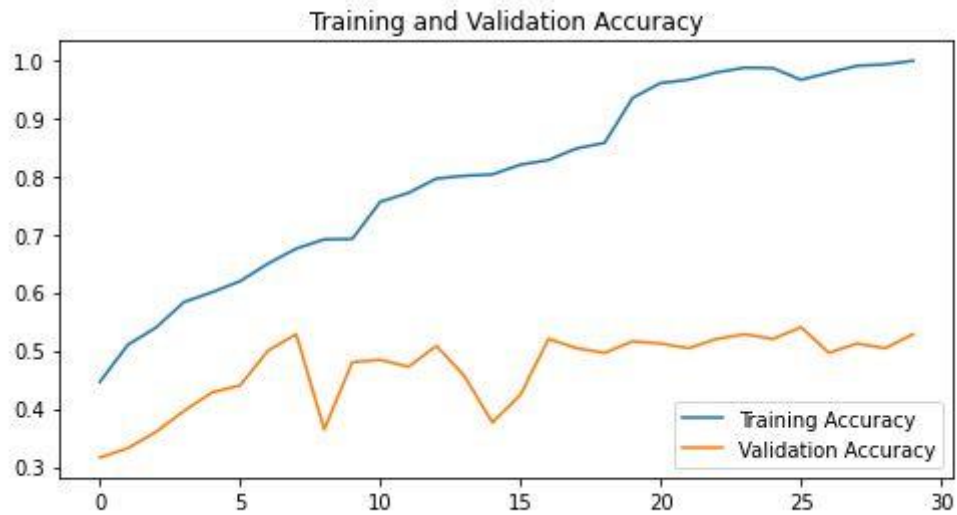


Figure 4. 4 Train and Validation Accuracy on LSTM Model

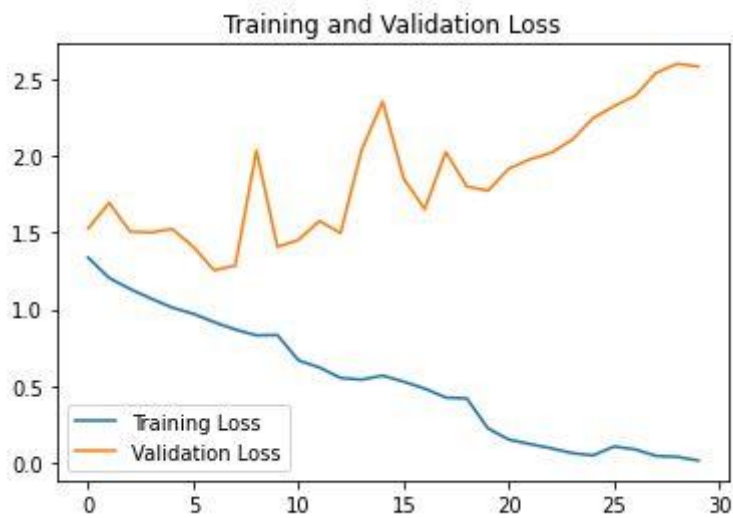


Figure 4. 5 Train and Validation Loss on LSTM Model

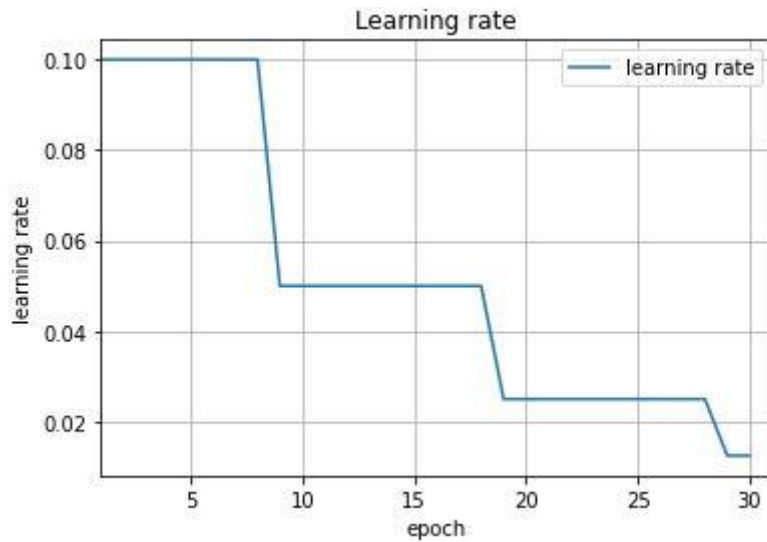


Figure 4. 6 learning rate of LSTM model

4.3 Prediction

We used 10 frames of human activity of 5 categories to predict its class and the result is very acceptable. Every time it shows very acceptable result expect some cases. Which can be overcome by train model with more data. For hardware limitation we used only 15000 images. But it is still showing a good result while predicting model with new data. In below figures some prediction shown.

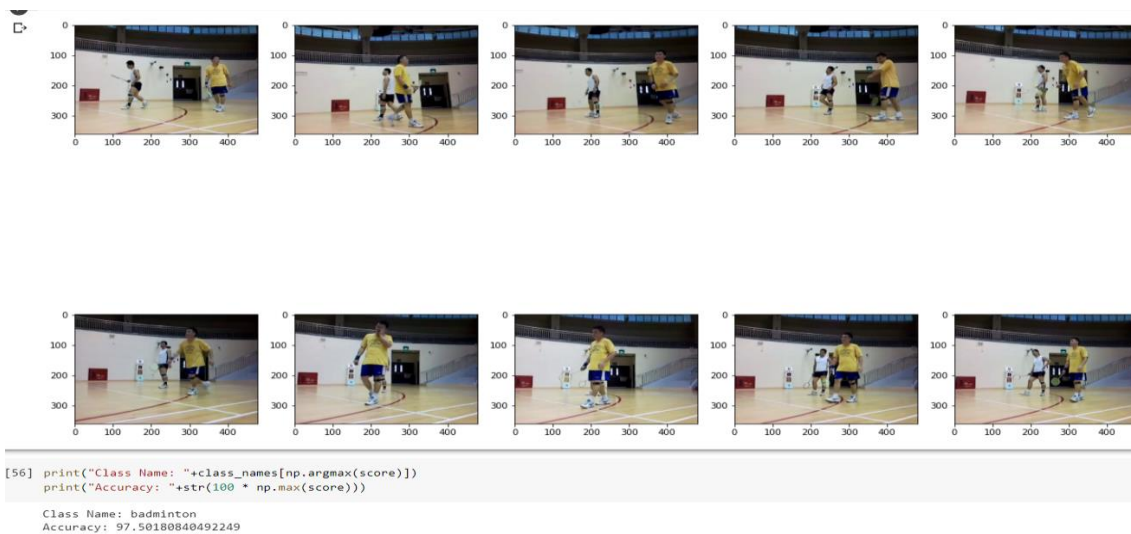


Figure 4. 7 Prediction 1

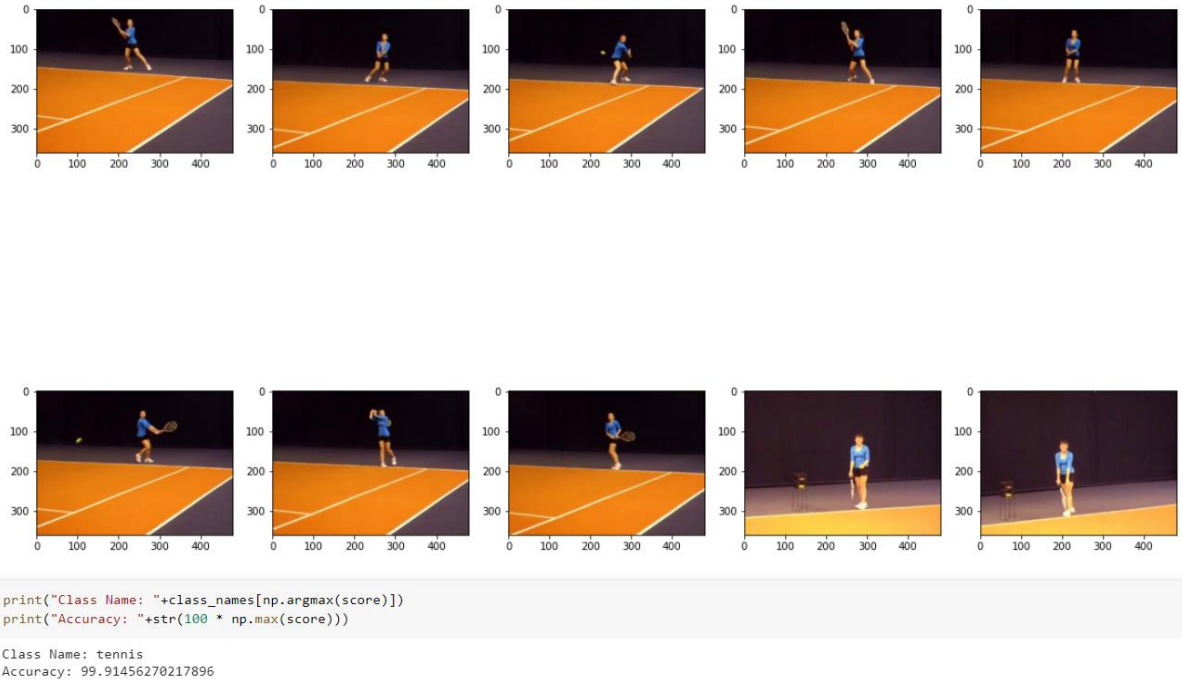


Figure 4. 8 Prediction 2

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Findings and Contributions

We collect data from YouTube which is almost 160 gigabytes then we pre-processed that video so that we can use it to train our model. We make frames from that video. We also used data augmentation so that video angle or zooming will not affect any uncertainty. We train vgg16 model with the data and not used any pre trained model to extracting features. We reduced learning rate in both CNN and LSTM training using step decay method.so that it can learn everything in an optimal rate.

5.2 Conclusion

In this study we start with a data set of videos then we convert it to images then perform data preprocessing to reduce noisy data. After that we extract feature from those images so our model can learn sequence so when we give a new data it can predict which human activity is perform in that data. We also archive a good accuracy 88% for this work which is remarkable results.

In Future we can use a large data set of large number of activities with a high computational power. We can improve our model with different architecture. We can also develop a web or mobile application using this model to detect human activity.

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Appendix -A

List of Abbreviation

CNN- Convolutional Neural Network

RNN- Recurrent Neural Network

LSTM- Long Short-Term Memory

DNN- Deep Neural Network

SGD- Stochastic Gradient Descent

Appendix –B

Plagiarism Report

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