B.TECH PROJECT REPORT-II

Yoga Guru: A Study of Pose Estimation and Machine and Deep Learning Methods For Yoga Pose Correction

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Proof of Conference

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INTERNATIONAL CONFERENCE
on
INTELLIGENT COMPUTING AND SECURITY: A PARADIGM SHIFT
(IICS2021)
Organised by
Department of Master of Computer Application
G.L. Bajaj Institute of Technology & Management, Greater Noida
December 17th - 18th, 2021

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Important Dates

Paper Submission Started:	15 September, 2021
Submission deadline:	15 November, 2021
Notification of acceptance:	5 December, 2021
Submission deadline for revised papers:	10 December, 2021
Date of Conference:	17-18 December, 2021

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CERTIFICATE

Certified that Ms./Mr./Dr. Dhananjay Sharma

from Delhi Technological University, Delhi

has participation / presented paper entitled Deep-Learning for Self-Learning in Yoga and Fitness: A Literature Review

in Two Days Springer Sponsored Intelligent Computing and Security: A Paradigm Shift (IICS2021) on December 17th - 18th 2021 *organized by Department of Master of Computer Applications, G.L. Bajaj Institute of Technology & Management Greater Noida, (U.P.) India.*

Convener	Conference Chair	General Chair
Dr. Sanjeev Kumar	Prof. (Dr.) Madhu Sharma Gaur	Prof (Dr.) Rajeev Agrawal

Problem Statement

01 HEALTH

With a rise in stress levels, obesity rates and health issues across the globe it has become imperative that we incorporate exercising as a part our daily routine

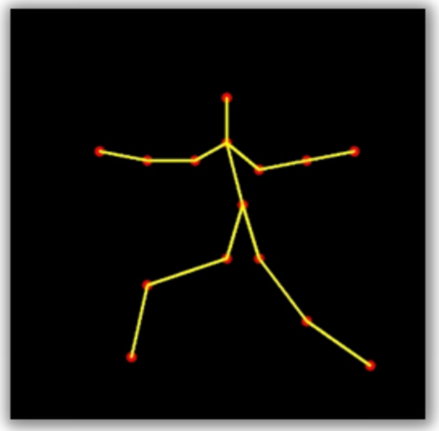
02 SCHEDULE

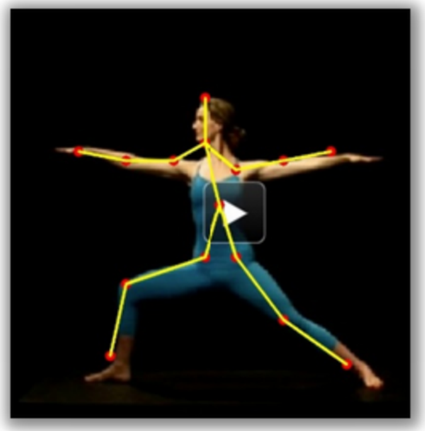
It is extremely difficult to afford a gym membership/private coach and match our schedule according to theirs on a daily basis.

03 PROPOSAL

Thus, we decided to propose a Deep Learning based solution that could solve the above problem.
A pipeline capable of analyzing a person's exercise posture and returning a feedback score!

Generic Pipeline





Dataset

- Five Yoga Pose Output Classes,
- Position and Color Augmentation to increase training data.
- Total 2000 images manually scraped
- Experimentation with 3 different dataset classes.

Pose Estimation

01 Backbone Architectures

Range from AlexNet, Fast R-CNN, Mask R-CNN, to feature pyramid networks. VGG and ResNet remain popular choice.

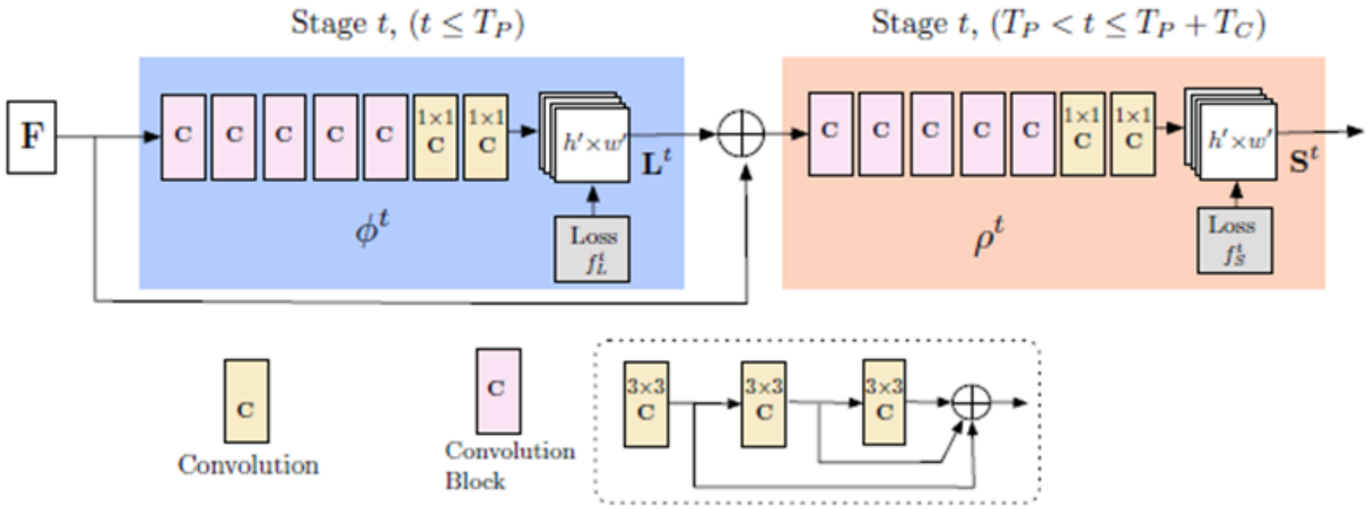
02 Loss Functions

Cross-Entropy loss, Mean Absolute Error, and Mean Squared Error are mostly used.

03 Evaluation Metrics

- Percentage of Correct Parts
- Percentage of Detected Joints
- Percentage of Correct Key-Points

Model	Year	Backbone Architecture	Approach	Loss Function	Evaluation Metrics	Training Datasets
DeepPose [30]	2014	AlexNet	Top-down	L2	PDJ, PCP	LSP, FLIC
DeeperCut [31]	2016	ResNet	Bottom-Up	L1, Cross-Entropy	AP, mAP, AUC, PCKh@0.5	MPII, COCO, LSP
Convolutional Pose Machines	2016	VGG	Top-down	L2	PCKh@0.1,PCKh@0.2, PCKh@0.5	FLIC, LSP, MPII
Rmpe: Regional Multi-Person Pose Estimation [32]	2017	VGG, ResNet	Top-down	L2	mAP	MPII, COCO
DensePose [33]	2018	FCN, Mask-RCNN	Bottom-up	Cross-Entropy	AP, PCP, GPS	COCO
High-Resolution Network (HRNet) [34]	2019	ResNet	Bottom-up	L2	AP, mAP, PCKh@0.5	MPII, COCO
Human Pose Estimation for Real-World Crowded Scenarios [35]	2019	ResNet	Top-down	L2	AP, OKS	CrowdPose, JTA

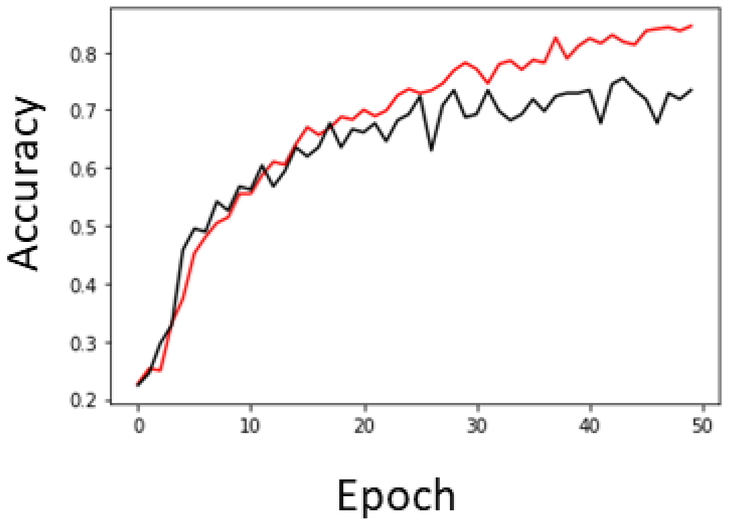


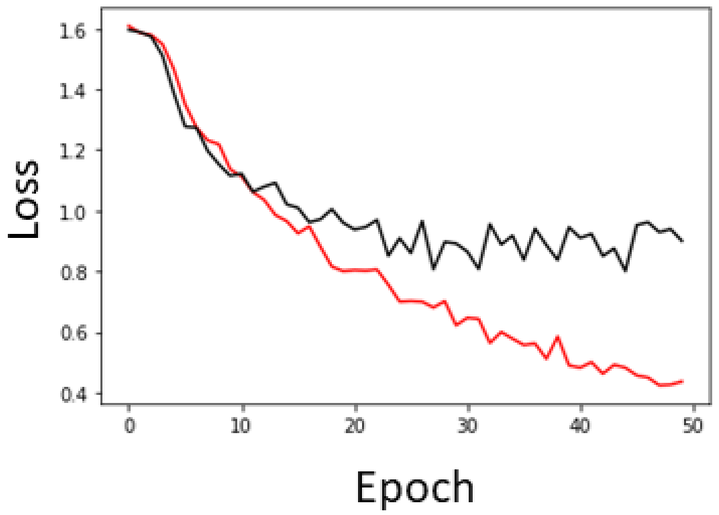
OpenPose Multi-Stage CNN Architecture

Estimating joint angles based on OpenPose indexing

Angle Name	Body Parts			MPII Label Index
elbow-r	Right Shoulder	Right Elbow	Right Wrist	[2,3,4]
elbow-l	Left Shoulder	Left Elbow	Left Wrist	[5,6,7]
knee-r	Right Hip	Right Knee	Right Ankle	[8,9,10]
knee-l	Left Hip	Left Knee	Left Ankle	[11,12,13]
neck-r	Head	Neck	Right Shoulder	[0,1,2]
neck-l	Head	Neck	Left Shoulder	[0,1,5]
leg-r	Chest	Right Hip	Right Knee	[14,8,9]
leg-l	Chest	Left Hip	Left Knee	[14,11,12]
back	Head	Neck	Chest	[0,1,14]

CLASSIFICATION TECHNIQUES

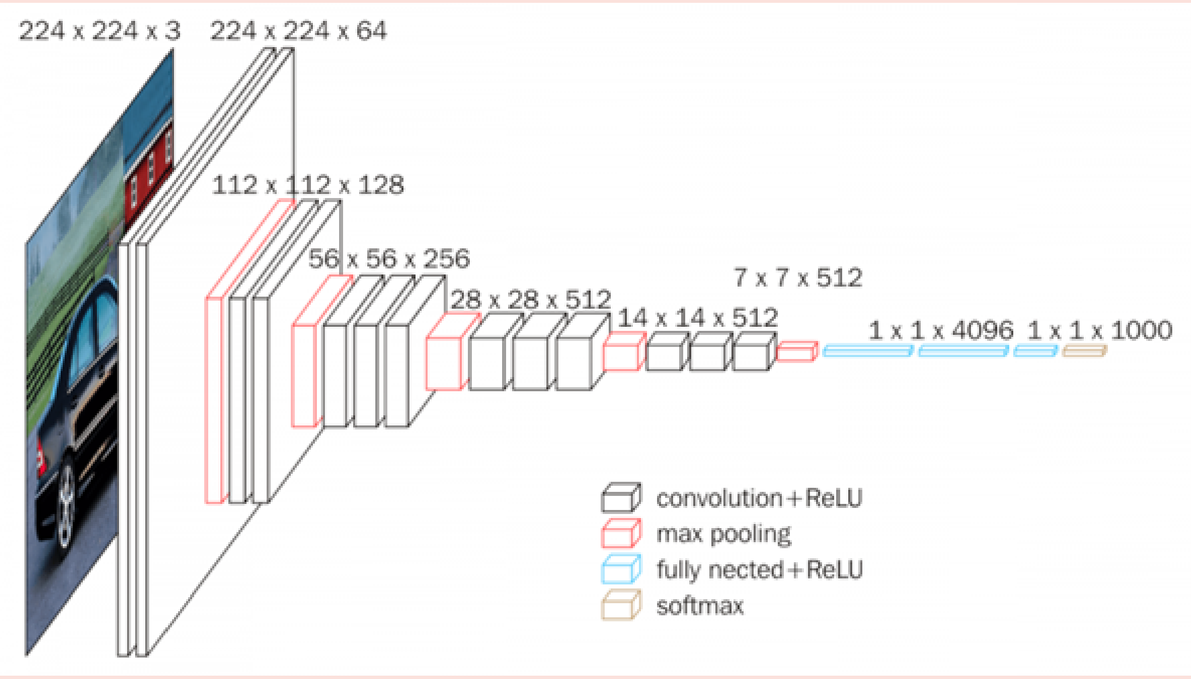


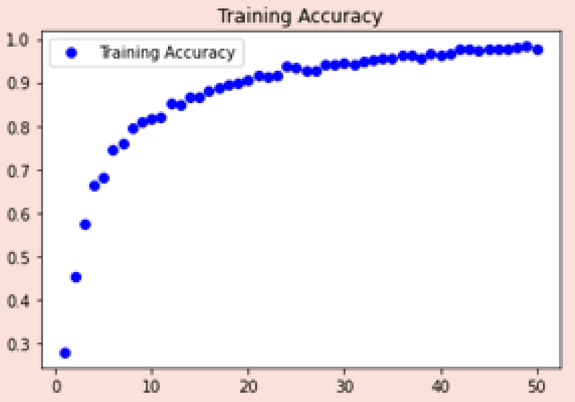


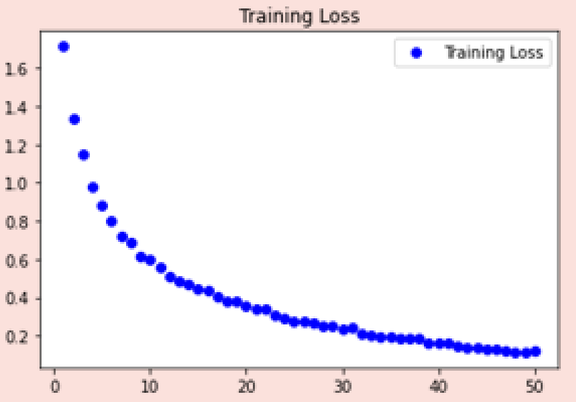

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 72, 72, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 36, 36, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 34, 34, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 17, 17, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 15, 15, 128)       147584
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 7, 7, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 6272)              0
_________________________________________________________________
dense (Dense)                (None, 64)                401472
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 325
=================================================================
Total params: 642,629
Trainable params: 642,629
Non-trainable params: 0
_________________________________________________________________
```

Custom Convolutional Neural Network

TRANSFER LEARNING: VGG - 16







OTHER CLASSIFIERS

```
sns.lineplot(x = nb, y = acc)
```

```
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```

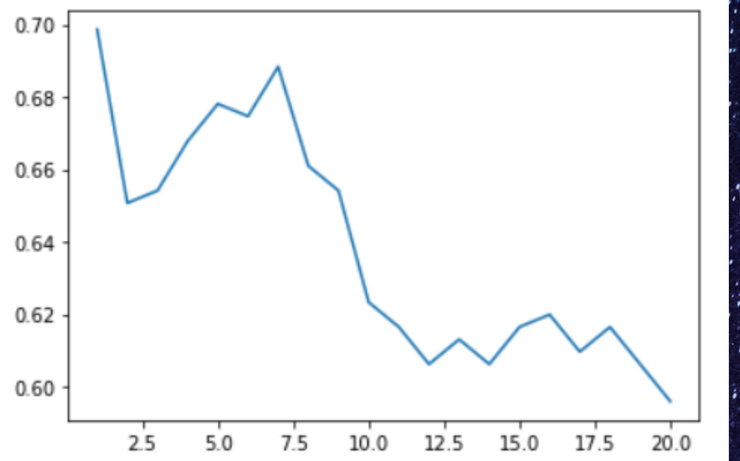

KNN (Acc v/s N)

```
sns.barplot(x = kernels, y=acc)
```

```
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```

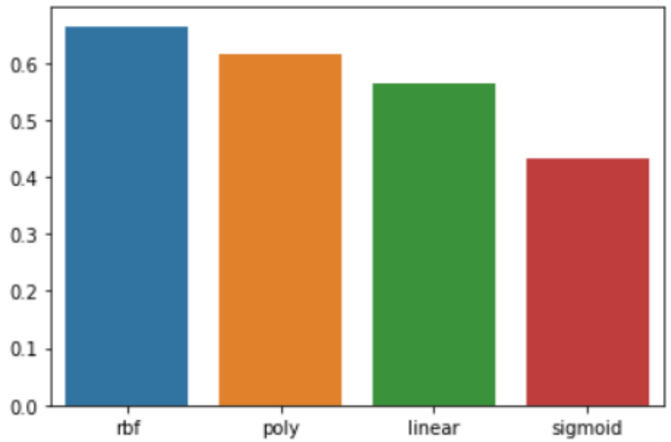

SVM (Acc v/s Kernel)

```
sns.lineplot(x = md, y = acc)
```

```
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```
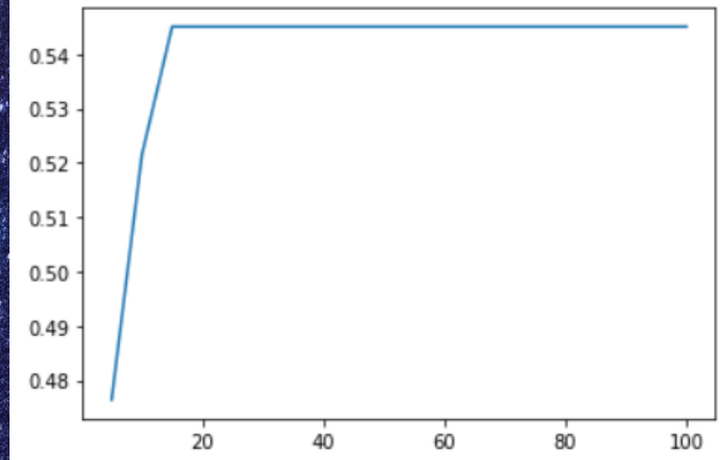
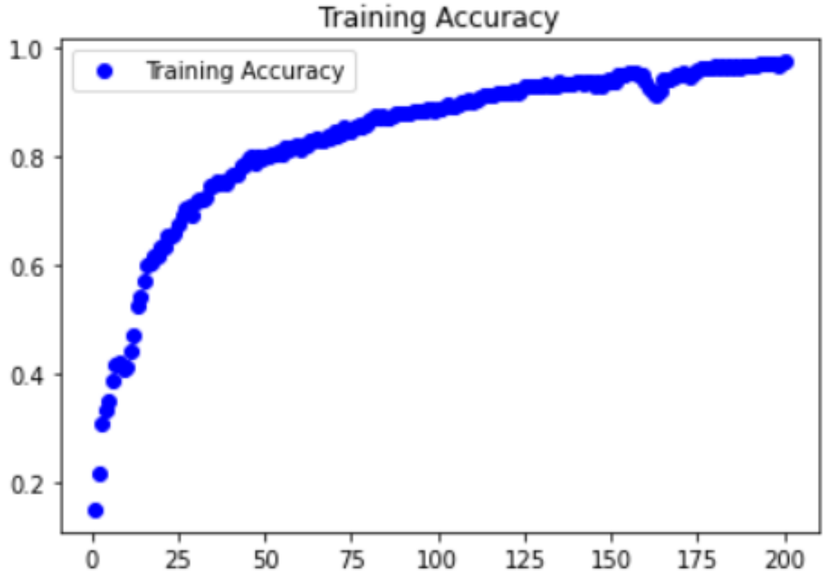



DT (Acc v/s Depth)

```
plt.show()
```



ANN (Acc v/s Epochs)

```
sns.lineplot(x = ne, y = acc3)
```

```
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```
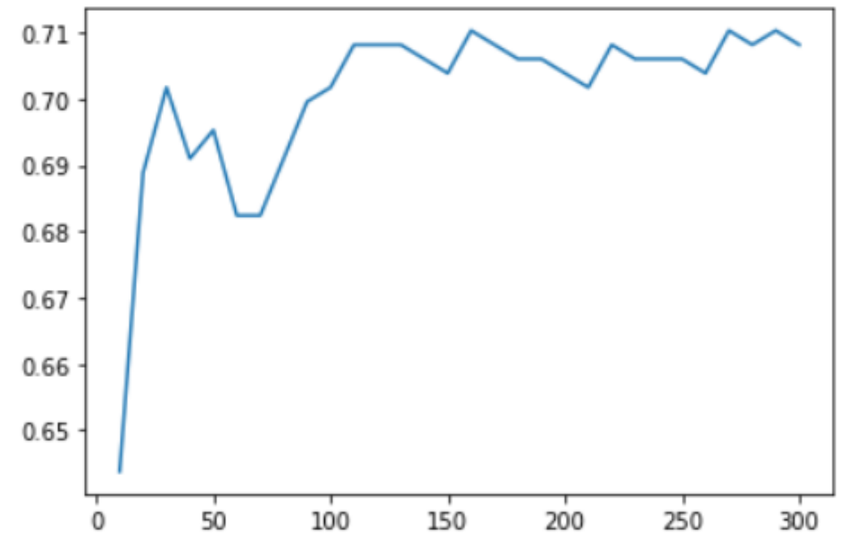
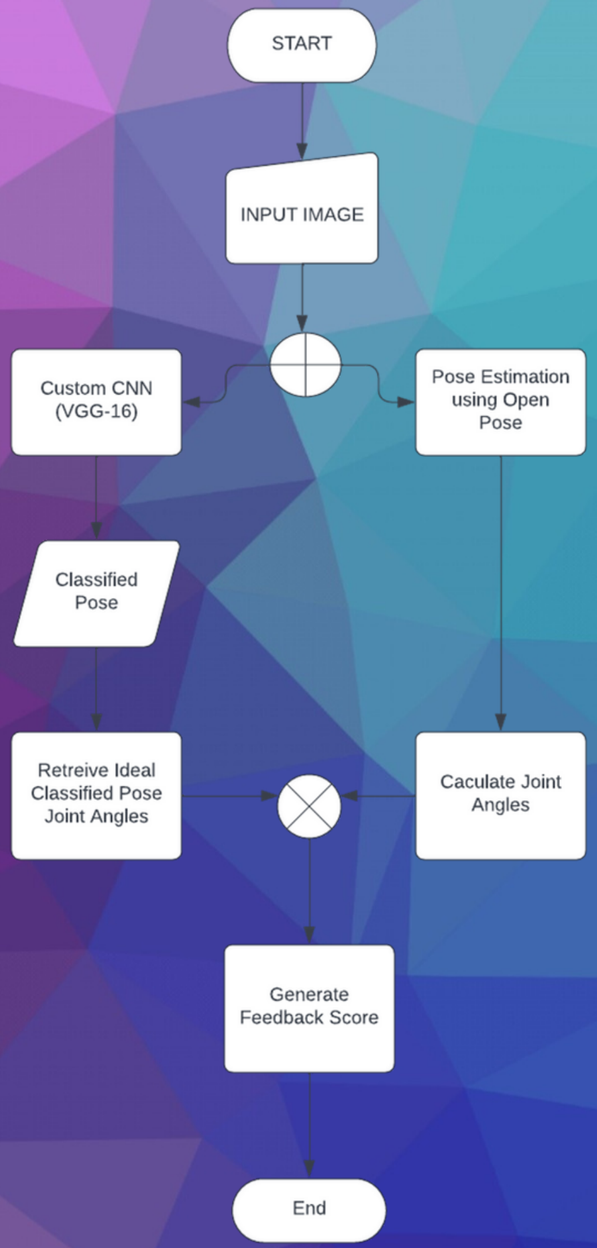
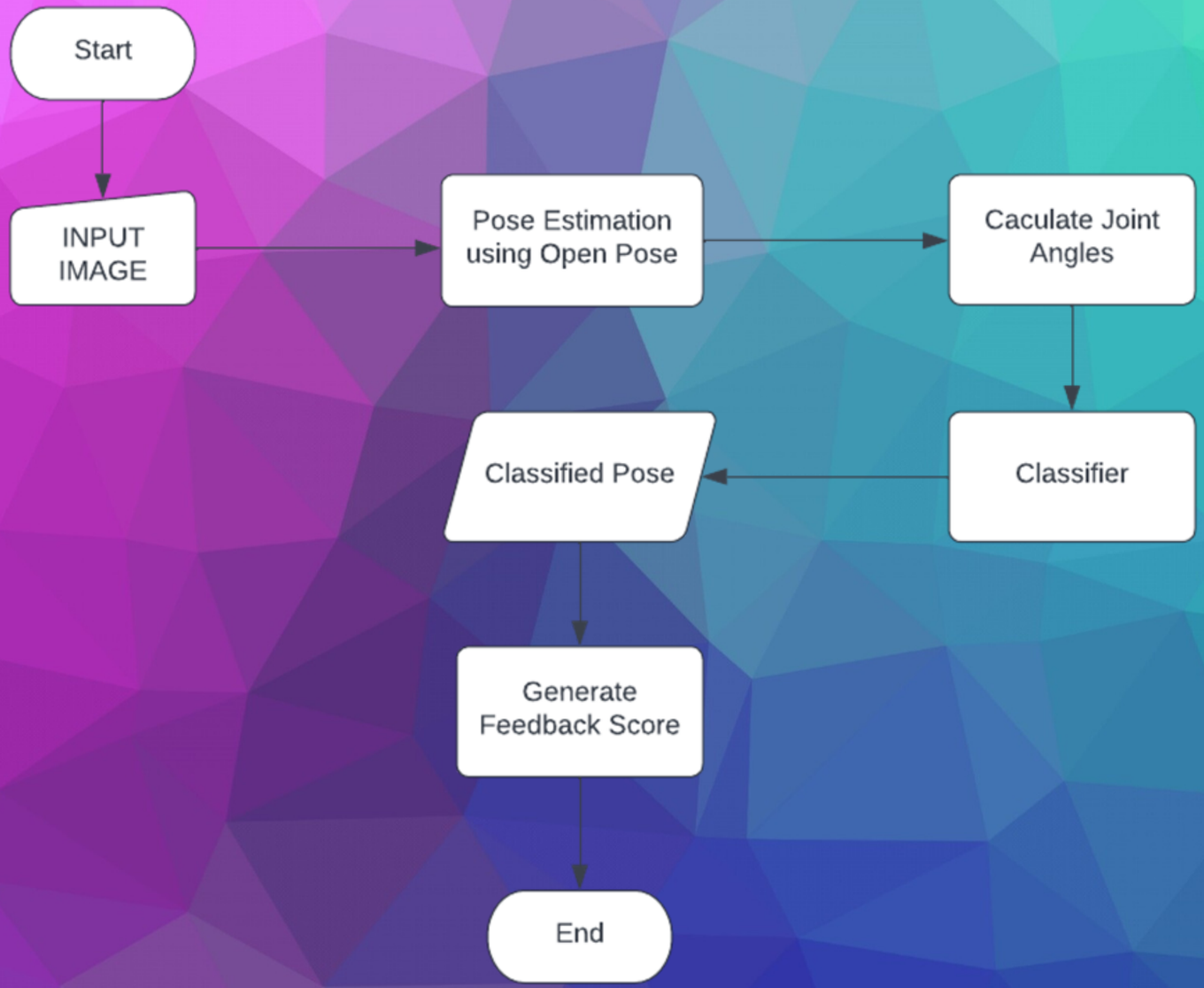



RF (Acc v/s N Trees)

THE TWO FLOWS



YOGA GURU FULL SCALE PIPELINE



YOGA GURU LIGHTWEIGHT PIPELINE

RESULTS

BY THE NUMBERS

Datasets	Train Accuracy	Test Accuracy
Plain Images	98.32%	93.56%
Pose Estimation on black background	85.21%	56.44%
Super imposed Images	98.06%	91.47%

Dataset Wise CNN

Model Structure	Train Accuracy	Test Accuracy
ReLu(16,12), Softmax(5)	73%	64%
ReLu(16,12, 8), Softmax(5)	78%	64%
ReLu(20, 16,12, 8), Softmax(5)	85%	64%
ReLu(20, 20, 16,12, 8), Softmax(5)	92%	66%
ReLu(24, 20, 20, 16,12, 8), Softmax(5)	97%	65%

Various ANNs

Algorithm	Best Test Accuracy
KNN	69.86%
SVM	66.43%
ANN	66.78%
Decision Tree	54.50%
Random Forest	71.03%

Best Test Accuracies

YOGA GURU




Here is Your Output

Predicted Pose	Warrior2

Score	8	10

Try Again ?

Output in the Flask App

Conclusion

1. Highlighted the importance and need for such a product
2. Summarised cutting edge pipelines, pose detection algorithms
3. Experimented with and analyzed various Machine learning and deep learning algorithms to suit our needs
4. Presented two product alternatives according to user's needs and equipments

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THANK YOU !

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