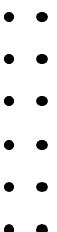




Natural Human-Computer Interface Based on Gesture Recognition with YOLO to enhance user experience



MOMINA LIAQAT ALI

OUTLINE

01

Introduction

02

Literature Review

03

Gesture Recognition

04

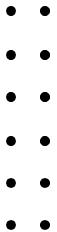
Natural HCI Design

05

Results

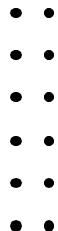
06

Conclusion &
Future Work



01

INTRODUCTION





INTRODUCTION



Hand Tracking & Gesture
Recognition



Human Computer Interaction
in Virtual Reality



Challenges



YOLO Based Solution





INTRODUCTION



Hand Tracking & Gesture Recognition

Enables computers to recognize and Respond to hand movements.

- Gained popularity during COVID-19.
- Demand for gesture recognition technologies is growing.
- Applications go beyond education to industries like automobile and healthcare.





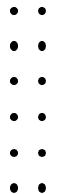
INTRODUCTION



HCI in Virtual Reality

VR Systems usually consist of 5 elements and three layers.

- VR system consists of:
 - VR Engine
 - Software & Database
 - Input/Output Devices
 - Users
 - Tasks
- VR system unfolds across:
 - System Layer
 - Middle Layer
 - Application Layer



INTRODUCTION

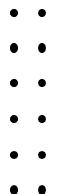


Challenges

Precision, Real-time responsiveness, adaptability and seamless Design.

.

- Precision:
 - To ensure reliable interaction by accurately interpreting hand movements.
- Real-time Responsiveness:
 - Timely response to optimize overall user experience.
- Adaptability & seamless Design:
 - Maintaining platform compatibility and user-friendliness while smoothly integrating hand tracking into a variety of applications





INTRODUCTION

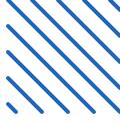


YOLO

YOLO based gesture recognition system.

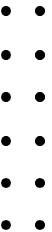
- For accurate gesture recognition, we used YOLO architecture.
- Using the object detection feature of YOLO to accurately recognize and comprehend hand gestures in a variety of settings.

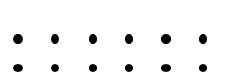




02

LITERATURE REVIEW





Object Detection Algorithms

1

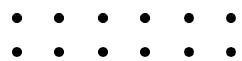
Single Stage Object Detectors

2

Two Stage Object Detectors

- Region Proposals
- Classification

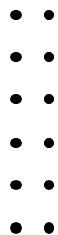




BUT...

Computationally Expensive

Require large labeled data



: : : : :

Object Detection Algorithms

1

Single Stage Object Detectors

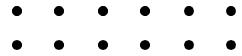
- No Region Proposal Stage
- Direct Prediction

2

Two Stage Object Detectors

- Region Proposals
- Classification

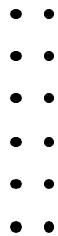




WHY YOLO?

Less Computation Cost

Real-time Performance



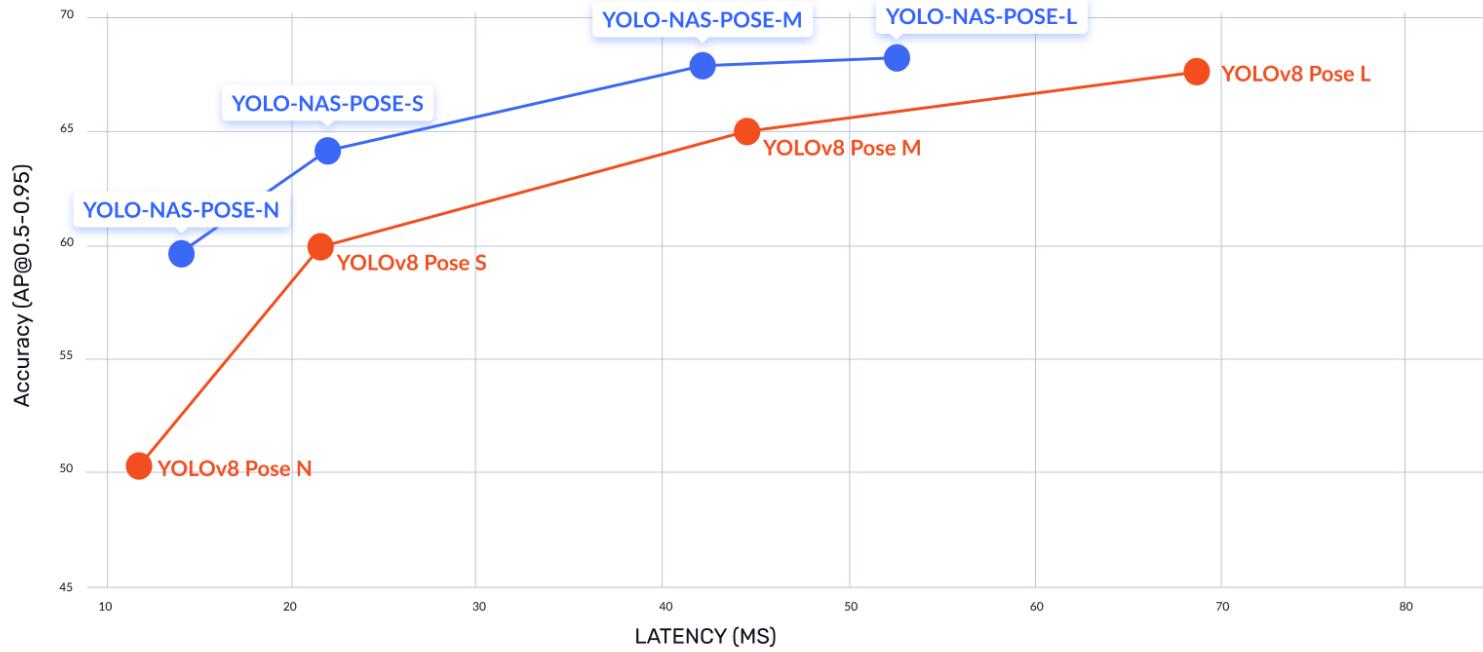


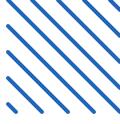
Image Credits: <https://www.linkedin.com/pulse/8-community-created-content-get-started-yolo-nas-pose-decial-omguc/>

Gesture Recognition

- Traditional Gesture Recognition Techniques
 - Hidden Markov Model (Chen et. al)
 - Orientation Histogram (Freeman et al.)
 - Finite State Machines (Hong et al.)
- Advanced Deep Learning Based Techniques
 - sEMG with CNN (Ozdemir et. al)
 - Depth camera with YOLOv3 (Yu et al.)
 - Transfer Learning (Savas et al.)

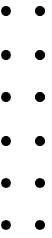
Posture Estimation

- Traditional Gesture Recognition Techniques
 - sEMG with CNN (Wang et. al)
 - Kinetic Sensors with DNN (Tang et al.)
 - DNN with Residual Connections (Bonab et al.)

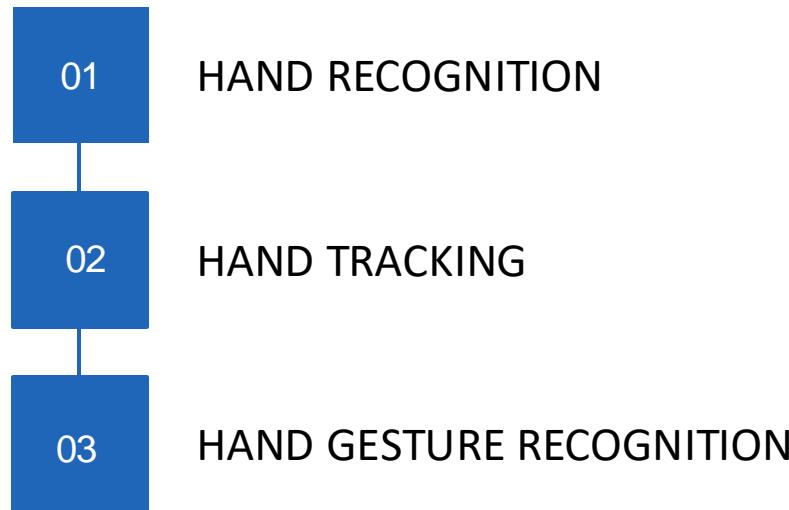


03

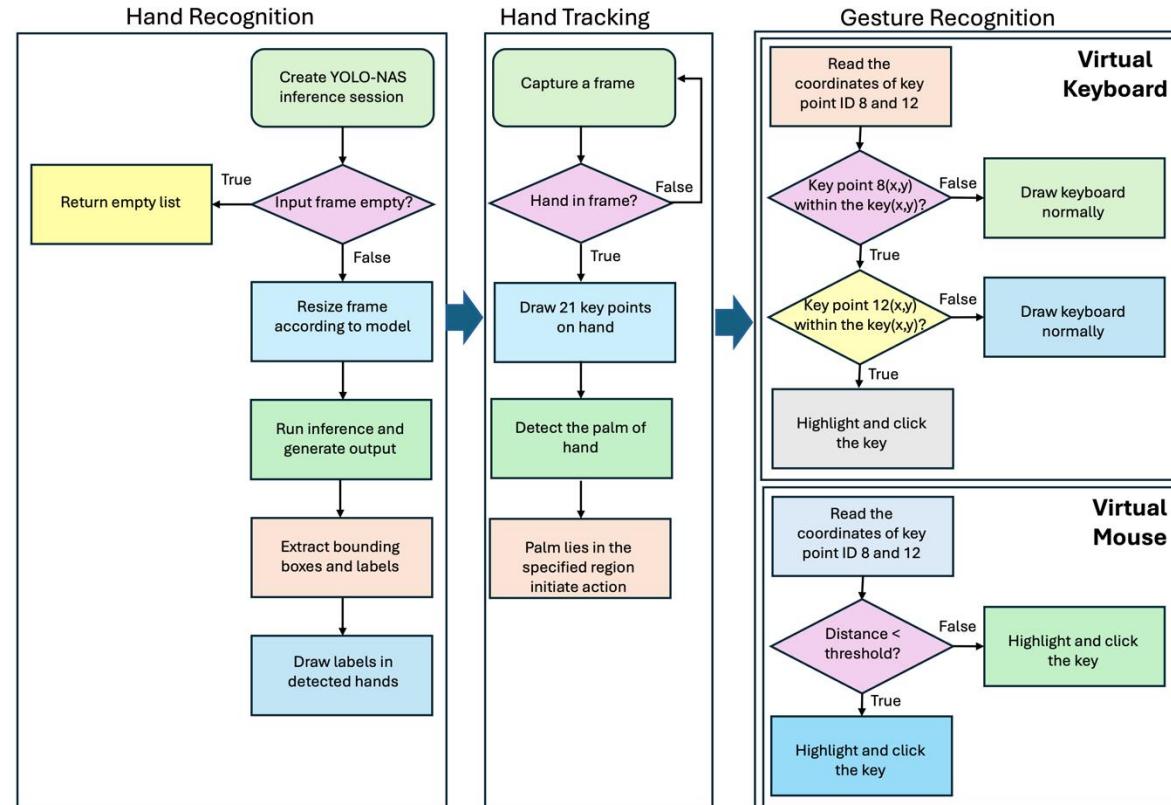
GESTURE RECOGNITION



THREE – STEP HAND GESTURE RECOGNITION

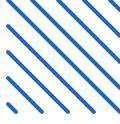


THREE – STEP PROCESS



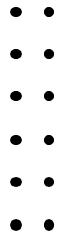
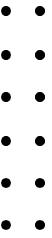
$$\cdot \quad distance = \sqrt{(x_{12} + x_8)^2 + (y_{12} - y_8)^2}$$





04

NATURAL HCI DESIGN



GESTURE RECOGNITION IMPLEMENTATION

-
- ```
graph TD; A[01] --- B[02]; B --- C[03];
```
- 01 DATA COLLECTION & PRE-PROCESSING
  - 02 GENERATING ANNOTATIONS
  - 03 MODEL TRAINING & FINE TUNING



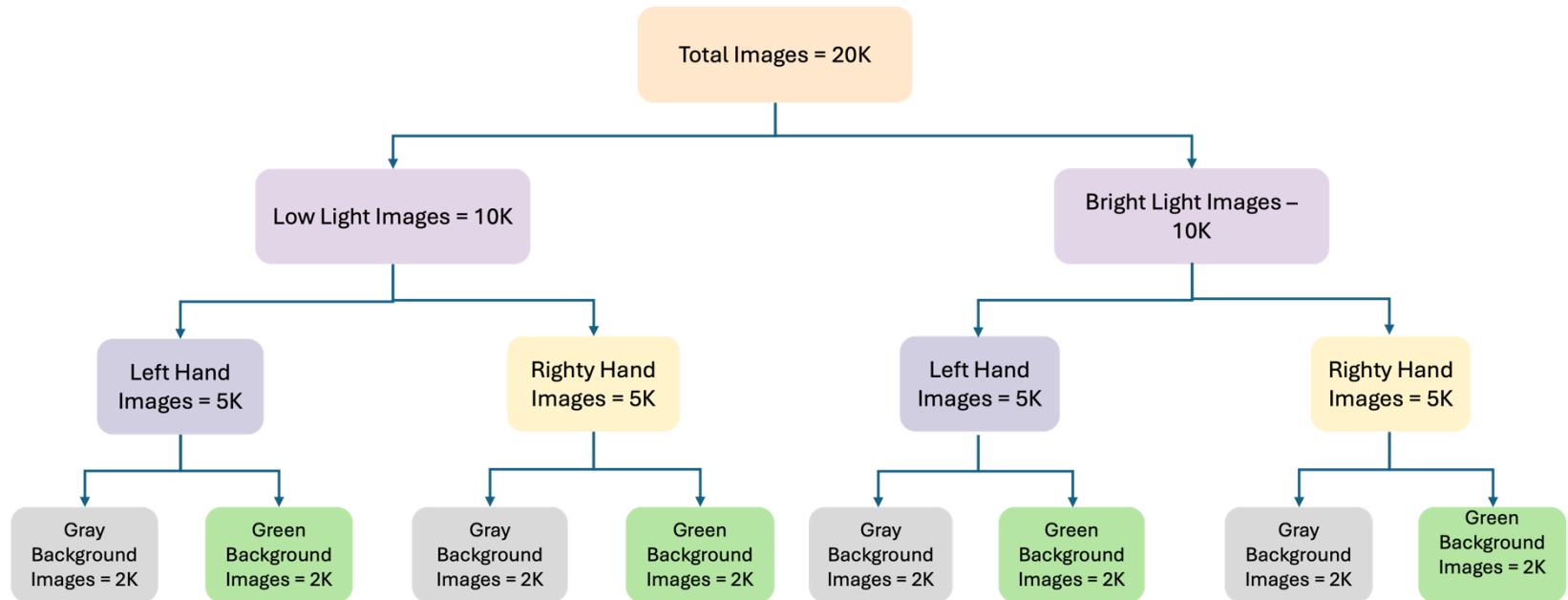
# DATA COLLECTION & PRE-PROCESSING

- Gathered data using webcam.
- Each image was of 2666x1488 pixels.
- Dataset contains 20K images.
- Augmentation techniques like flipping and grayscale were used .
- All images were taken with green screen background in low light and bright light conditions.



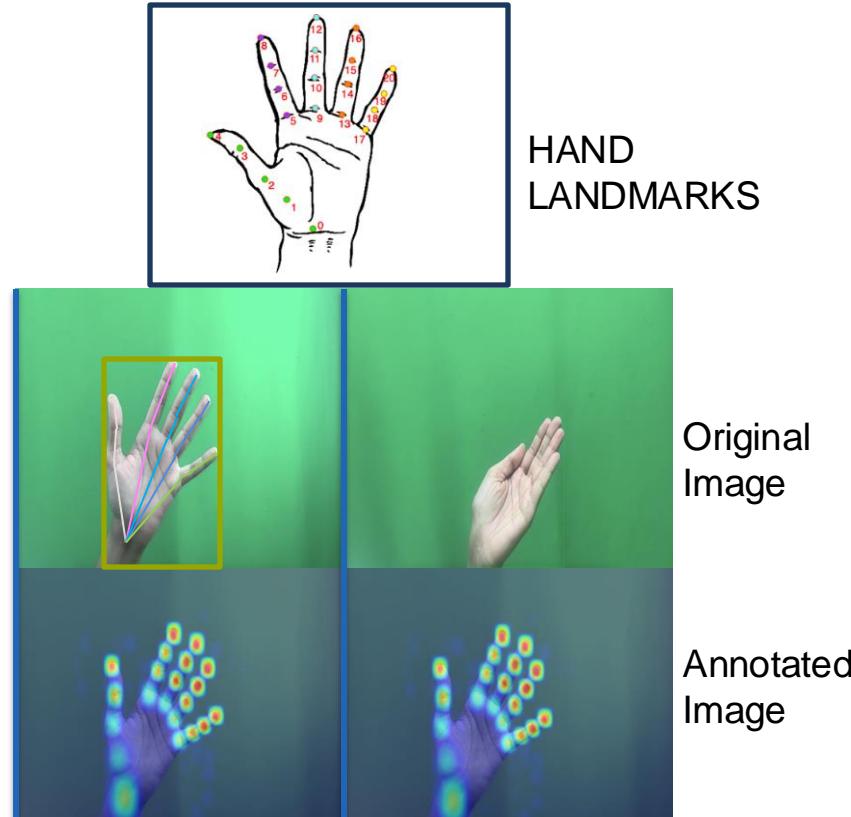
Sample Images from Dataset

# DATASET CONSTRUCTION TREE



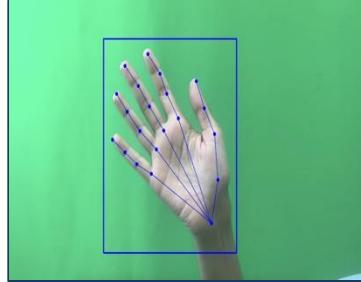
# GENERATING ANNOTATIONS

- Why not manual annotation?
- 21 key-points on human hand were annotated.
- MMPose uses RTMDet which is trained on 4 different hand datasets.
- RTMDet outperforms YOLO with 52.8% AP on COCO and 300+ FPS on an NVIDIA 3090 GPU.
- Used RTMDet-Nano for detection and RTMPose for posture estimation.
- Annotations were converted to json format.

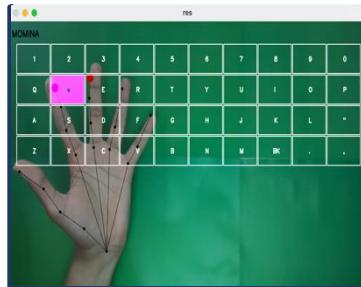


# MODEL TRAINING & FINE TUNING

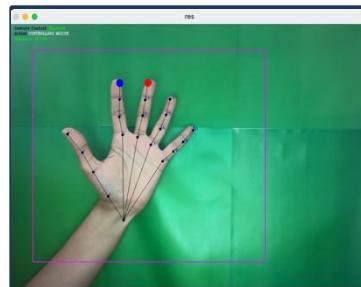
- Used YOLO-NAS Pose; a sibling model of YOLO-NAS.
- Famous model because of its capability of being a single-stage detector which makes it fast in real-time applications.
- YOLO-NAS Pose performs both detection and estimation of Pose in single pass.
- YOLO-NAS Pose is trained on COCO2017 Dataset.
- We fine-tuned the model on our dataset.



HAND LANDMARKS



KEYBOARD CONTROL



MOUSE CONTROL

# Model and System Details

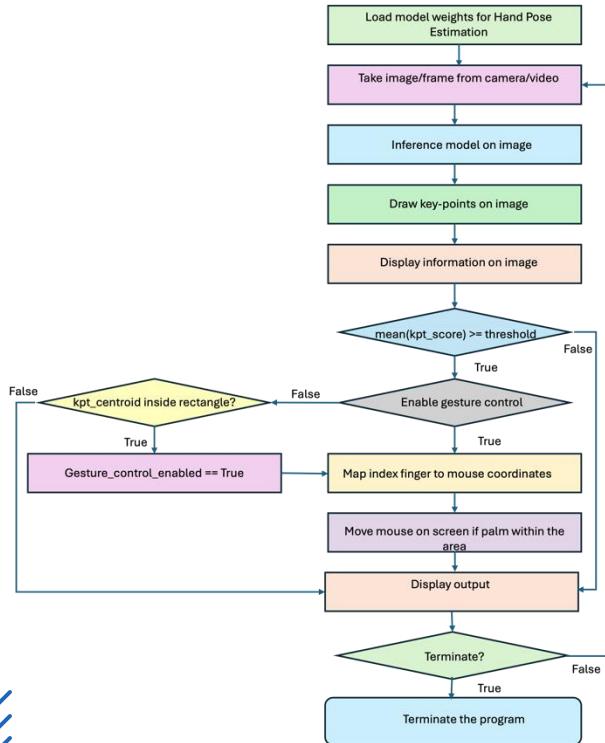
- $r = \max\left(\frac{640}{h}, \frac{640}{w}\right)$
- $\text{Updated\_height} = h * r$
- $\text{Updated\_width} = w * r$
- $\text{UpdatedKeypoint}_i = \text{originalKeypoint} * r$
- $\text{UpdatedBBox}_i = \text{originalBBox}_i * r$

| Configurations       | Value    |
|----------------------|----------|
| Epochs               | 10       |
| Learning Rate        | 0.001    |
| Optimizer            | AdamW    |
| Weight Decay         | 0.000001 |
| Batch size           | 32       |
| Iterations per Epoch | 439      |

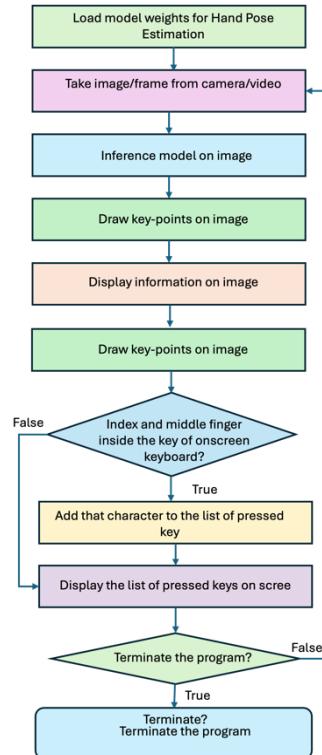
  

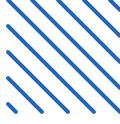
| Features                    | Details             |
|-----------------------------|---------------------|
| CUDA Cores                  | 7689 Cores          |
| CPU Memory                  | 24 GB @ 300 GBps    |
| Compute Performance<br>FP64 | 0.5 TFLOPS          |
| Compute Performance<br>FP32 | 30.3 TFLOPS         |
| Architecture                | NVIDIA Ada Lovelace |

# VIRTUAL MOUSE



# VIRTUAL KEYBOARD





- 
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- 

05

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- 

# RESULTS





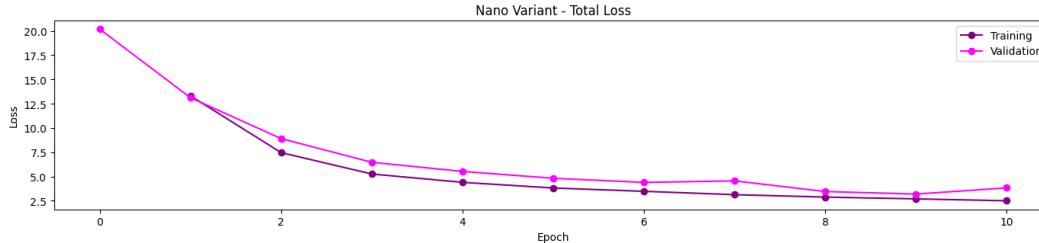
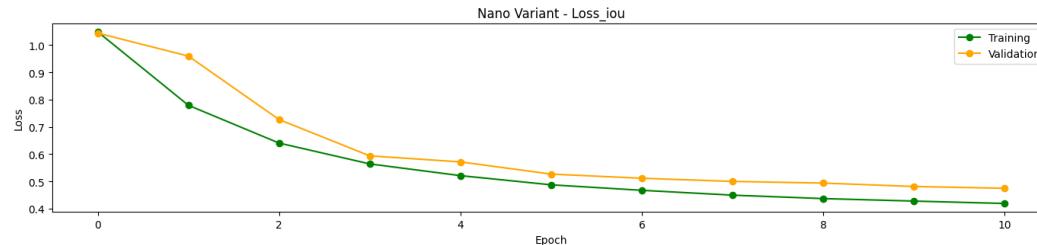
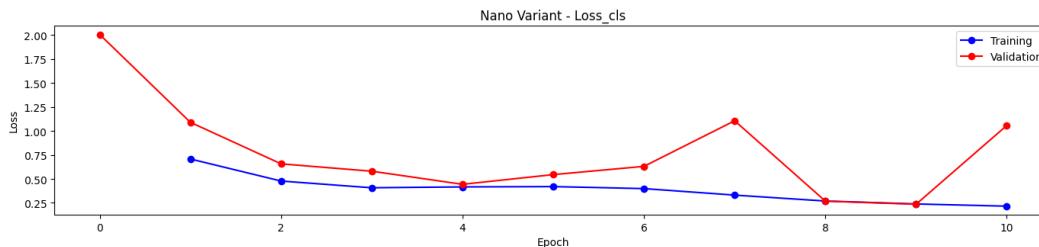
# RESULTS

- We created two instances of the dataset one had 5k images and named it as Dataset A and other had 20k images and names it as Dataset B.
- Each of these models were trained for 10 Epochs on both datasets A and B.
- We monitored AP and AR on each epoch and computed the Total loss, classification loss and IOU loss

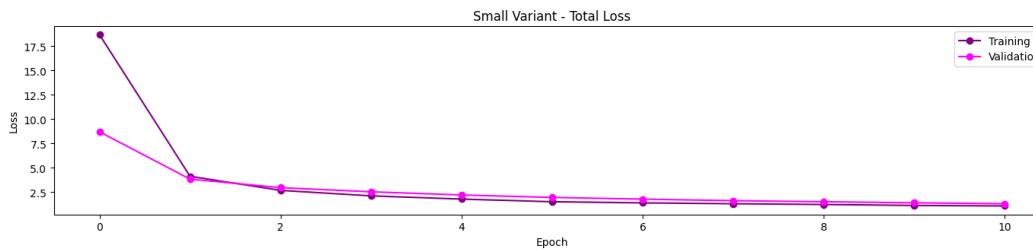
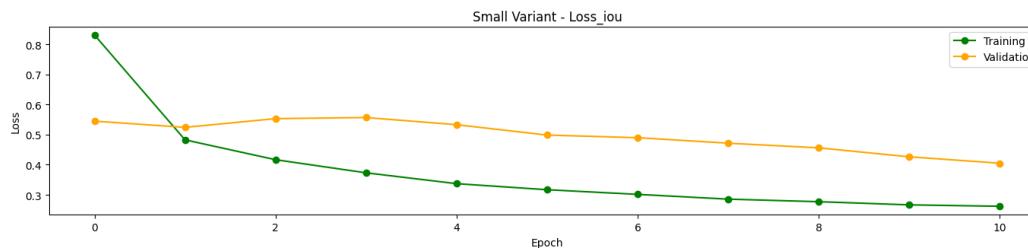
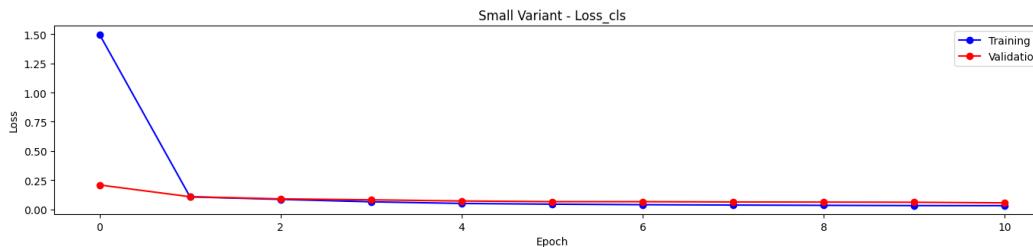
| <b>Model</b> | <b>No. of Parameters</b> |
|--------------|--------------------------|
| Nano         | 9,901,483                |
| Small        | 22.2 million             |
| Medium       | 58.2 million             |



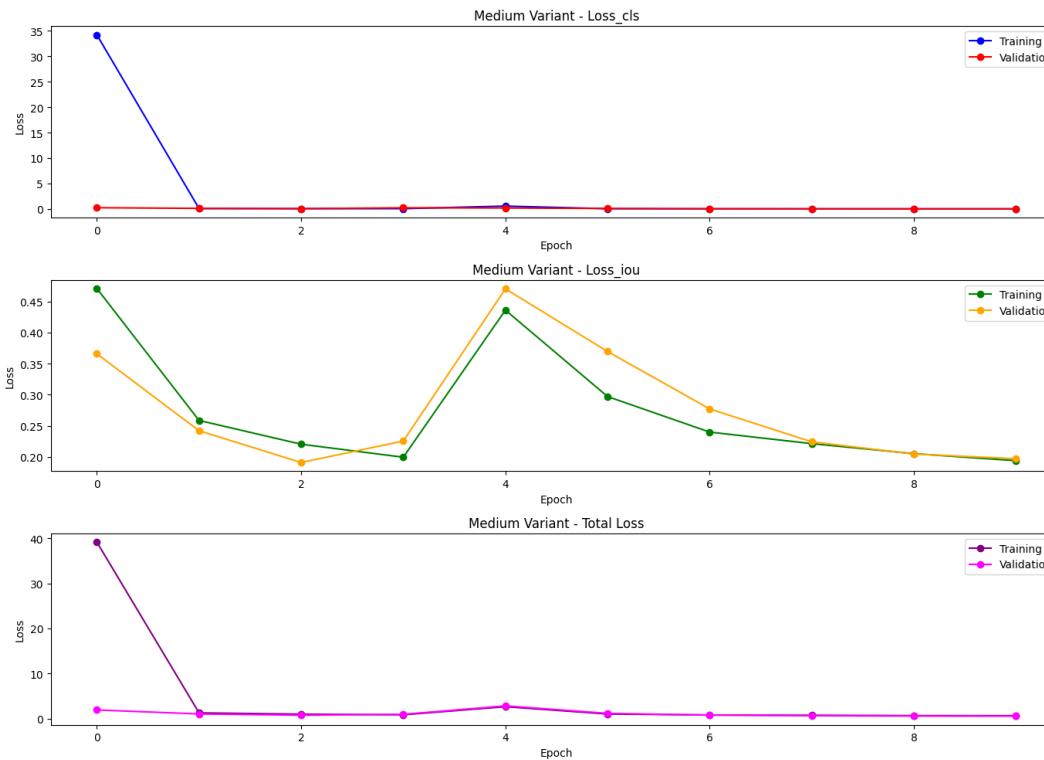
# NANO MODEL - DATASET A



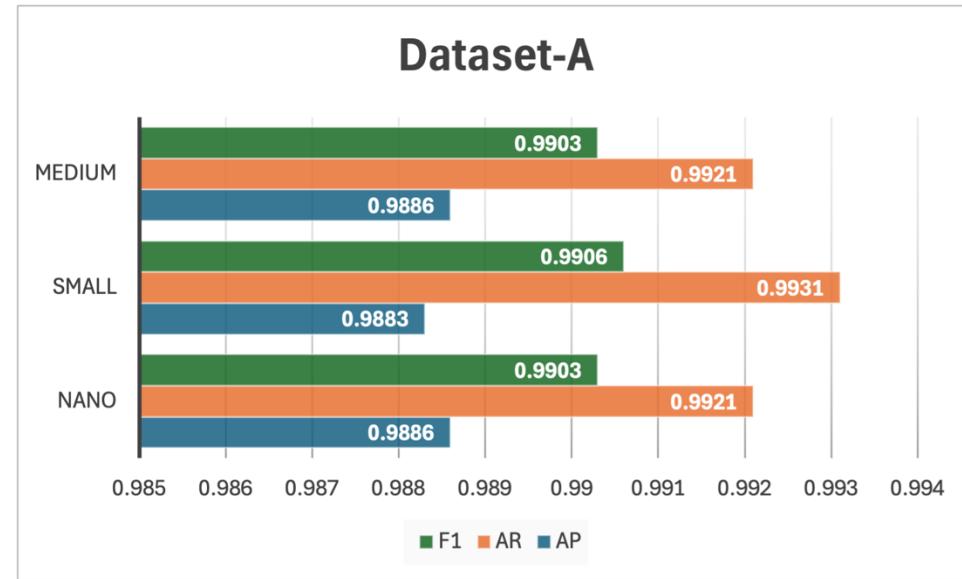
# SMALL MODEL - DATASET A



# MEDIUM MODEL - DATASET A

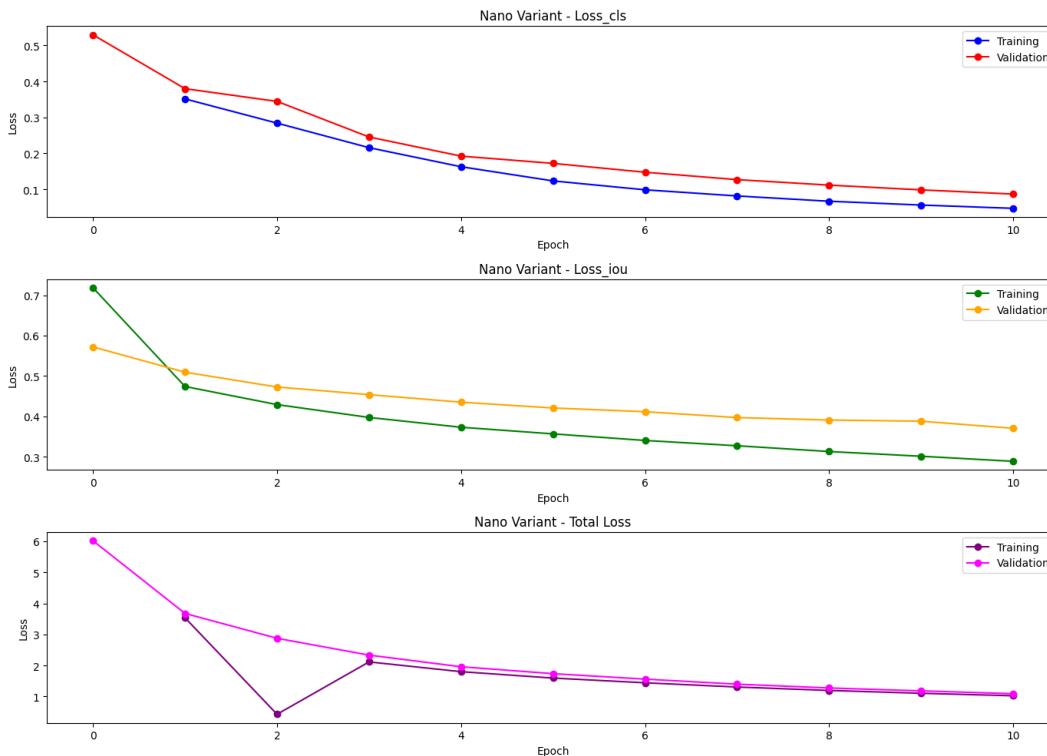


# COMPARISON OF THREE VARIANTS OF THE MODEL ON DATASET - A

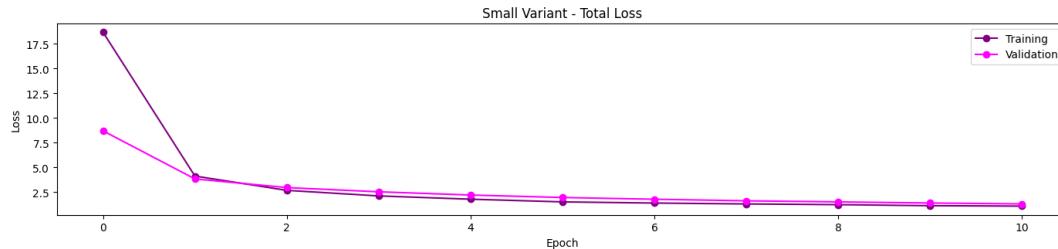
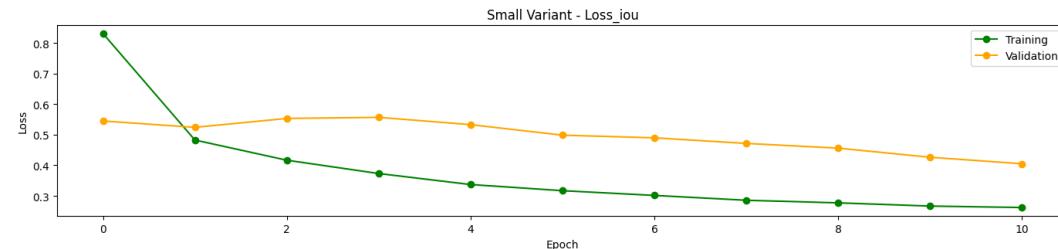
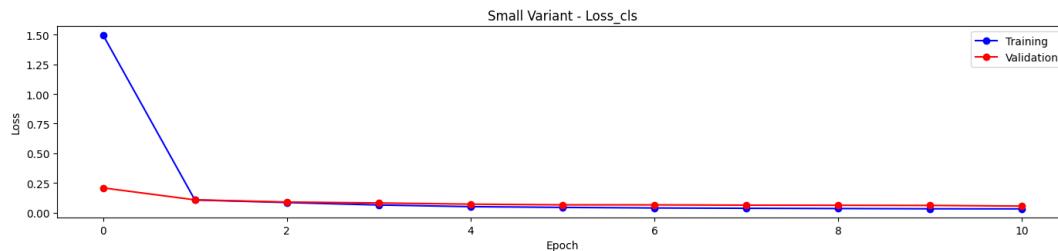


| Model Variant | AP     | AR     | F1     |
|---------------|--------|--------|--------|
| NANO          | 0.9886 | 0.9921 | 0.9903 |
| SMALL         | 0.9883 | 0.9931 | 0.9906 |
| MEDIUM        | 0.9886 | 0.9921 | 0.9903 |

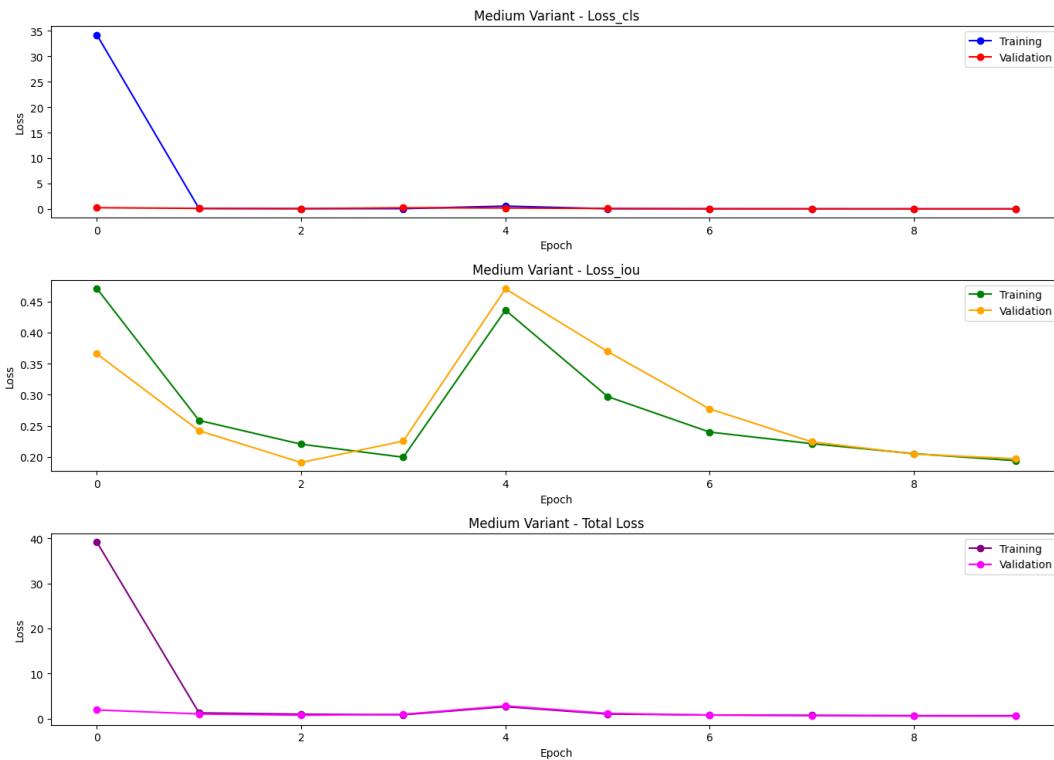
# NANO MODEL - DATASET B



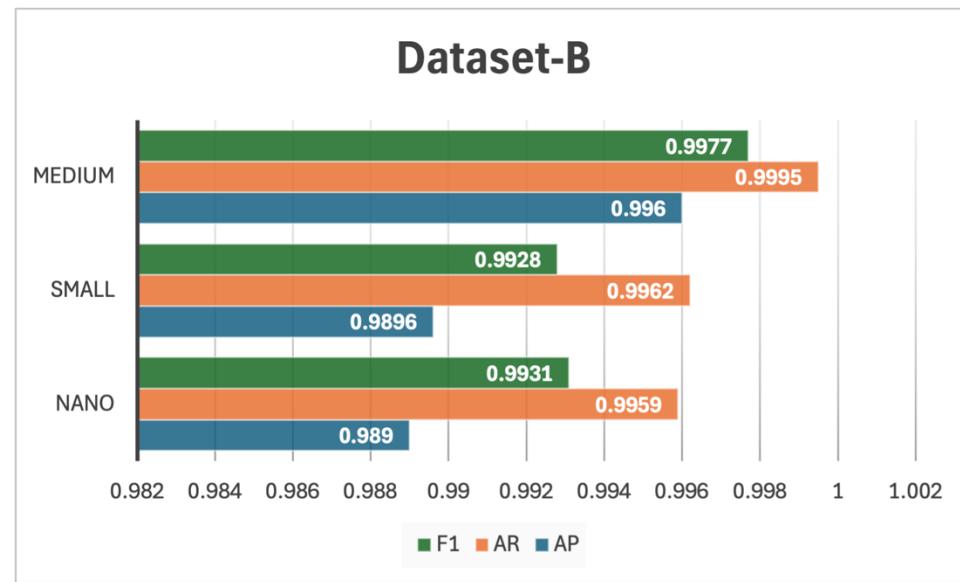
# SMALL MODEL - DATASET B



# MEDIUM MODEL - DATASET B



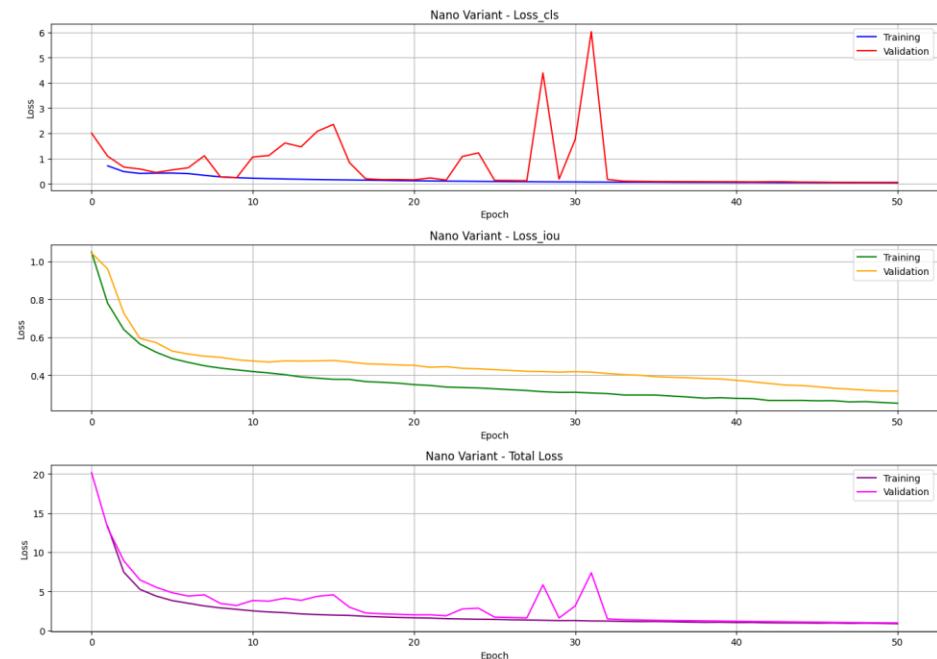
# COMPARISON OF THREE VARIANTS OF THE MODEL ON DATASET - B

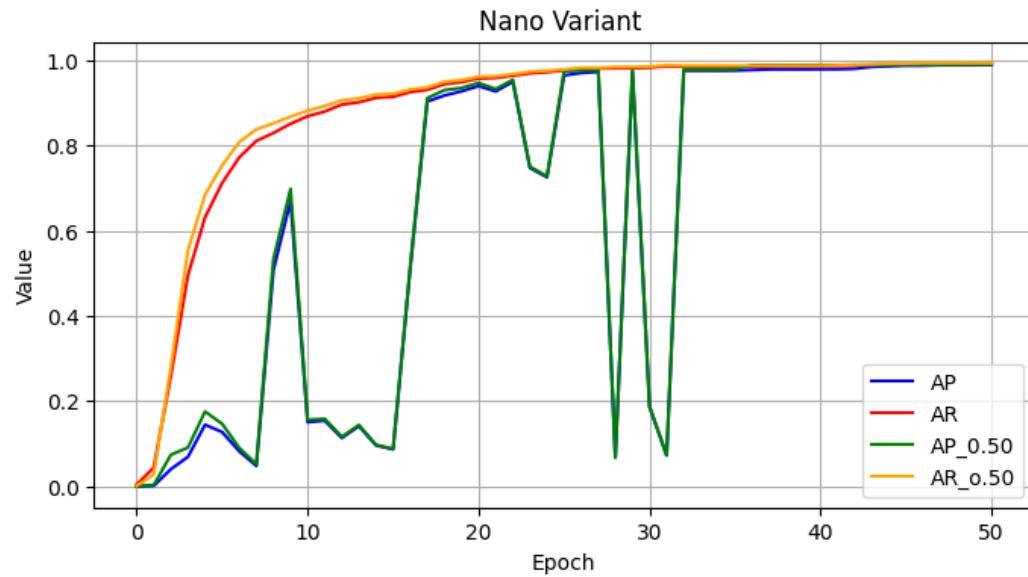


| Model Variant | AP     | AR     | F1     |
|---------------|--------|--------|--------|
| NANO          | 0.989  | 0.9959 | 0.9931 |
| SMALL         | 0.9896 | 0.9962 | 0.9928 |
| MEDIUM        | 0.996  | 0.9995 | 0.9977 |

# NANO VARIANT AS THE WINNER

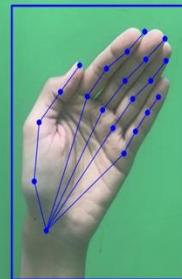
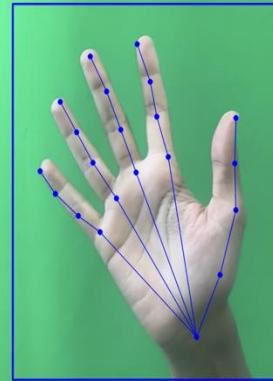
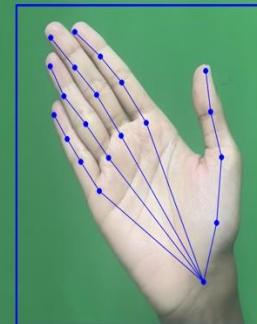
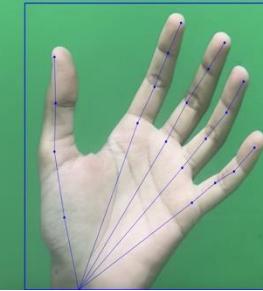
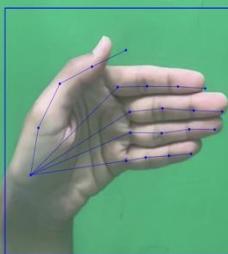
- From the results obtained on the datasets and from the literature, nano variant is the best choice for real-time processing when we deploy it on edge devices.
- We then trained Nano variant for 50 Epochs and we saw clear results of less overfitting when considering AP and AR metrices.





| Model | AP     | AR     | F1     |
|-------|--------|--------|--------|
| Nano  | 0.9886 | 0.9921 | 0.9903 |

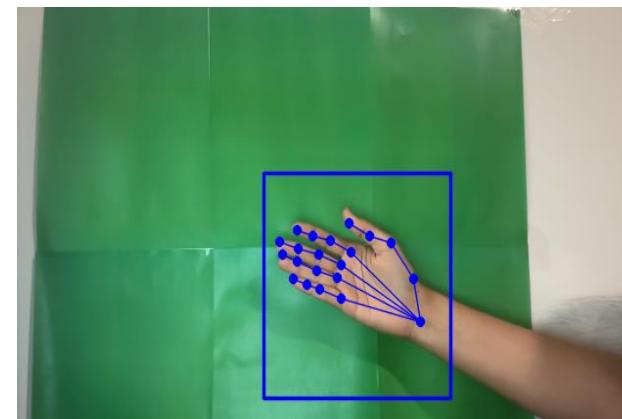
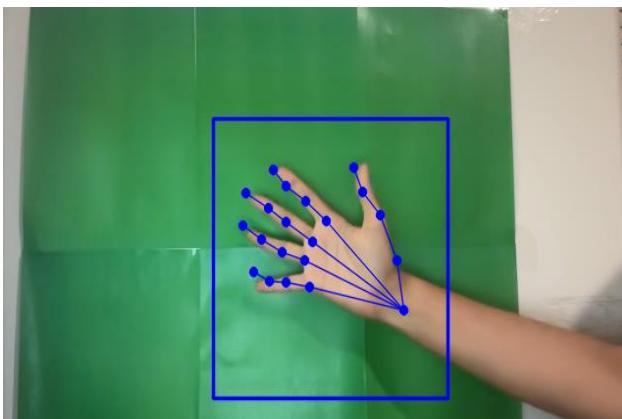
:::::::::: Predictions made by model on Test Data ::::::::::



::::::::::

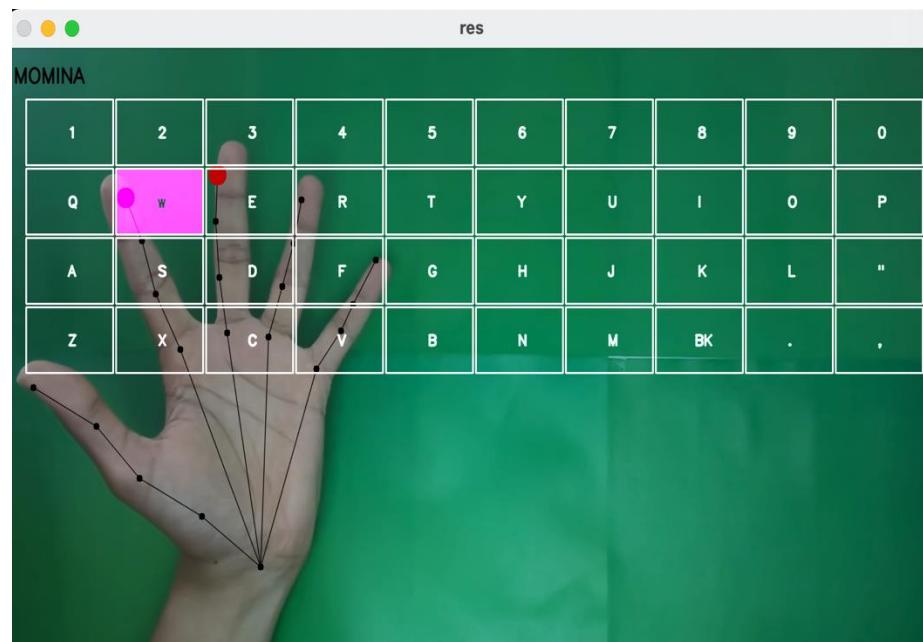
::::::::::

Predictions made by model on data with  
some degree of white background involved

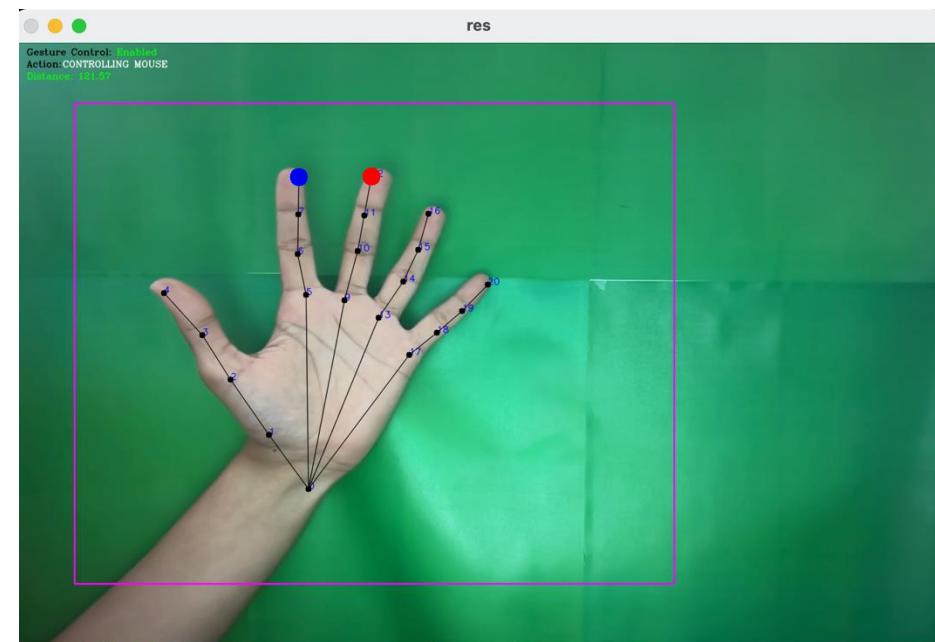




# Virtual Mouse and Keyboard in Action

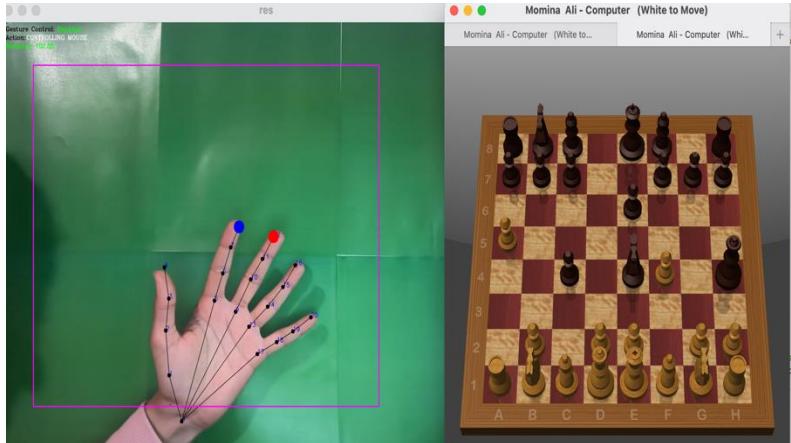


Virtual Keyboard

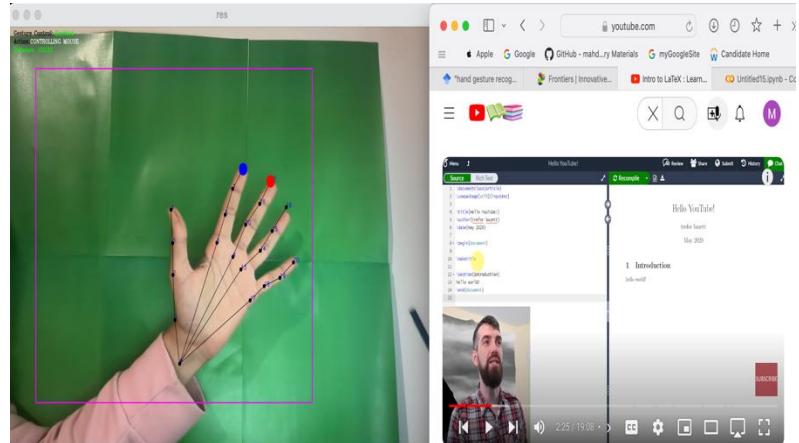


Virtual Mouse

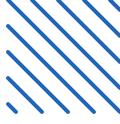
# USE CASES



Virtual control for playing chess on computer

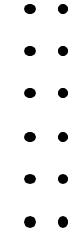


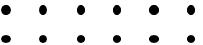
Remote control for media playback



06

# CONCLUSION & FUTURE WORK





# CONCLUSION



## FOCUS OF RESEARCH:

- Enhancing Human-Computer Interaction (HCI) in Virtual Reality (VR) by utilizing technology for gesture recognition and hand tracking



## VIABILITY DEMONSTRATION:

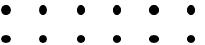
- Use of YOLO models in a virtual Human Computer Interface demonstrates its practicality and increases user engagement in virtual reality settings.



## REAL-WORLD APPLICATION:

- By connecting theory and practice, the use of virtual mouse and keyboard can greatly revolutionize the gaming and education industry.





# FUTURE WORK



## SUSTAINED IMPROVEMENT:

- More precision and versatile hand gestures will be added.



## IMPROVING VIRTUAL EXPERIENCE:

- To increase the frame-rate to give user a feeling of immersive control of mouse cloud interface will be made better and parallel processing of the frames will be achieved.



THANK YOU!

