# **ARCH TECHNOLOGIES**

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### **Review of the Project**

This project refers to the detection and distribution of brain tumors with the help of Yolov11.

#### I used:

- Yolov11 determines the object (finding the tumor in the figure).
- Sam2 (its own demo -ZIS of the tumor area).
- Sam2 and then used the tumors more precisely.

### **Study Material and References**

Below is the list of videos, tutorials, and articles I used to understand and complete the Brain Tumor Segmentation Project using YOLOv11 and SAM2:

### **■** 1. Yolov11 and SAM2 for Custom Instance Segmentation

#### YouTube Video:

Yolov11 and SAM2 for Custom Instance Segmentation - Code With Arohi <a href="https://www.youtube.com/watch?v=a7fHmqkUu5Q">https://www.youtube.com/watch?v=a7fHmqkUu5Q</a>

#### **Used for:**

- Learning how to train YOLOv11
- Understanding how to use SAM2 for segmentation
- Connecting YOLO results with SAM2

# Learning outcomes from video

Following are handwritten notes of YouTube video:

	te handwritten notes of TouTube video.
	Topic Name: Brain Tumos detection Video Bj: Code with Archi Tools: Yello 11, SAM2
7	Install Libraries
	> Install Ultresty tics > Install segment Anything Model > Use pip install for dependencies
	Prepare dataset:
	-> use Roboxflow or custom dataset.  -> Export da-la in Yollo Format.  -> Creat folder: Irain, val, test
-)	Train Yollo 114
	> Training data in vunildeteet Hein > Best weights gaved as "best pt"
7	Tect The Modell.
	brain tumos from predict  Jolder.

Integrate Yollo with SAM: - Import SAM

- Get bounding boxes from

- Get bounding boxes from

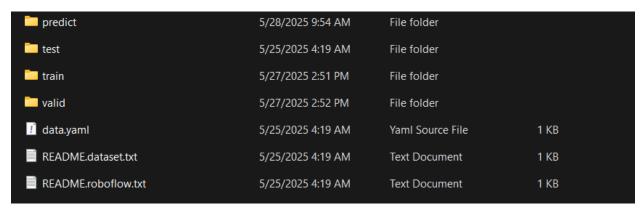
- Yollo result.

- Pass them to SAM For segmentation. Run Segmentations > Reg Run Sigmentation and sque output in runs Idetect / predict

## **Images and Diagrams.**

These are images of brain tumors before and after training.

### **Dataset Structure Diagram**

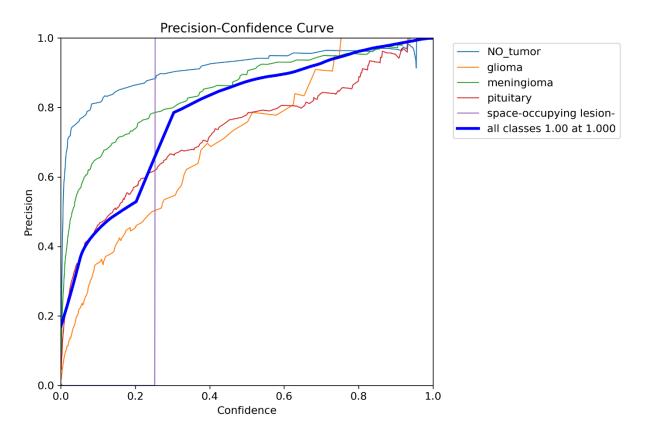


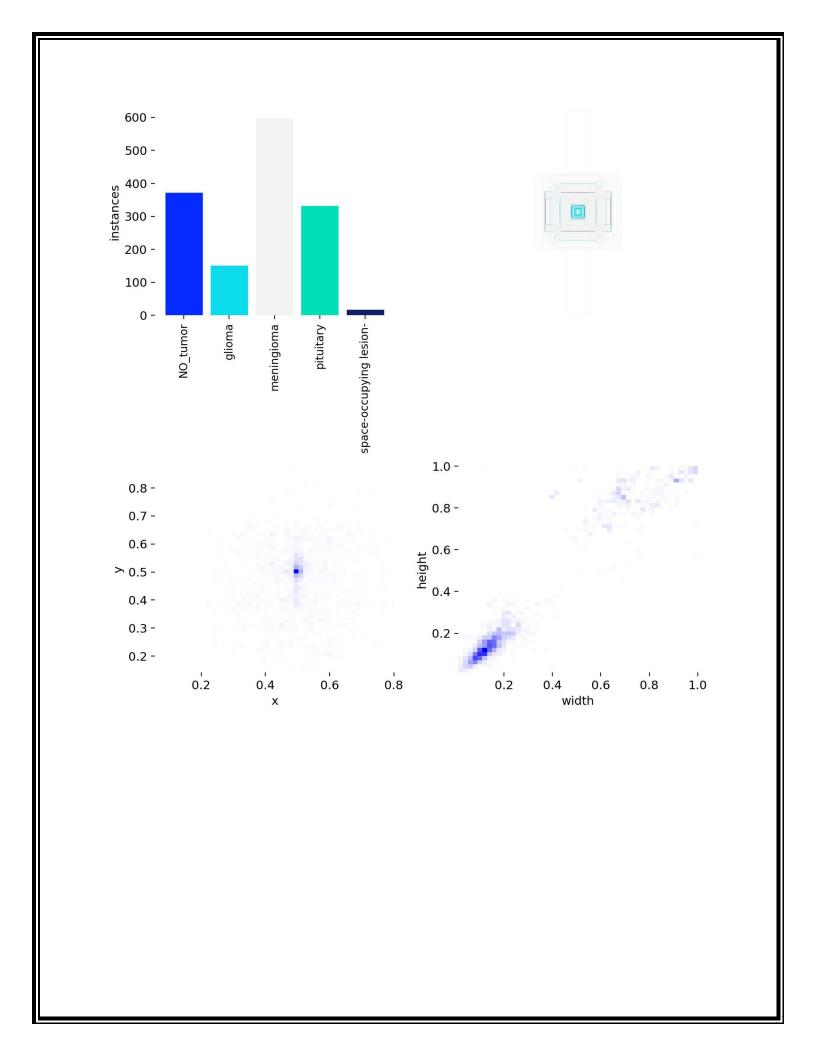
### **Dataset images:**



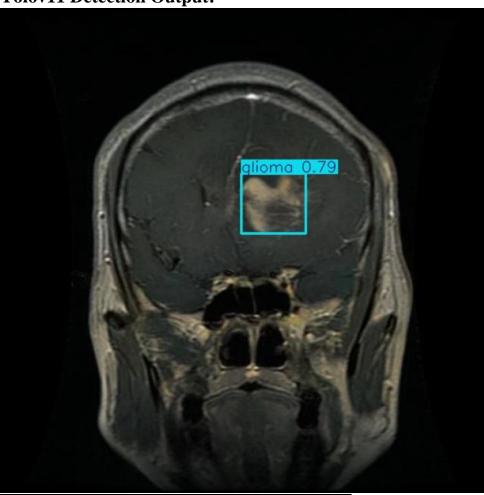
# Yolov11 Model Training Graph:

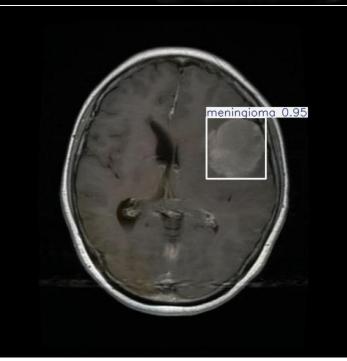
Epoch 15/15	GPU_mem ØG Class all	box_loss 0.7947 Images 395	cls_loss 0.6052 Instances 415	dfl_loss 0.9228 Box(P 0.819	Instances 2 R 0.573	Size 128: mAP50 0.596	100%  mAP50-95): 0.417	172/172 [01:25<00:00, 2.01it/s]   100%		
ochs completed in 1.455 hours.										
izer str	izer stripped from runs\detect\train11\weights\last.pt, 6.2MB									
izer stripped from runs\detect\train11\weights\best.pt, 6.2MB										
ating runs\detect\train11\weights\best.pt										
lytics 8	3.3.144 Pyt	thon-3.13.3	torch-2.7.0	+cpu CPU (	Intel Core(TM	4) i5-8350	U 1.70GHz)			
summary	/ (fused): 7	72 layers,	3 <b>,</b> 006 <b>,</b> 623 pa	rameters,	0 gradients,	8.1 GFLOP	S			
	Class	Images	Instances	Box(P	R	mAP50	mAP50-95):	100% 25/25 [00:13<00:00, 1.81it/s]		
	all	395	415	0.819	0.574	0.595	0.417			
	NO_tumor	115	116	0.926	0.978	0.98	0.788			
	glioma	30	36	0.608	0.306	0.364	0.173			
m	neningioma	144	148	0.889	0.864	0.927	0.691			
	pituitary	106	111	0.673	0.721	0.706	0.433			
-occupyi	ng lesion-	1	4	1	0	0.00106	0.000745			
: 0.3ms preprocess, 17.1ms inference, 0.0ms loss, 1.3ms postprocess per image										
ts saved to runs\detect\train11										
\Users\M	1ishah>									



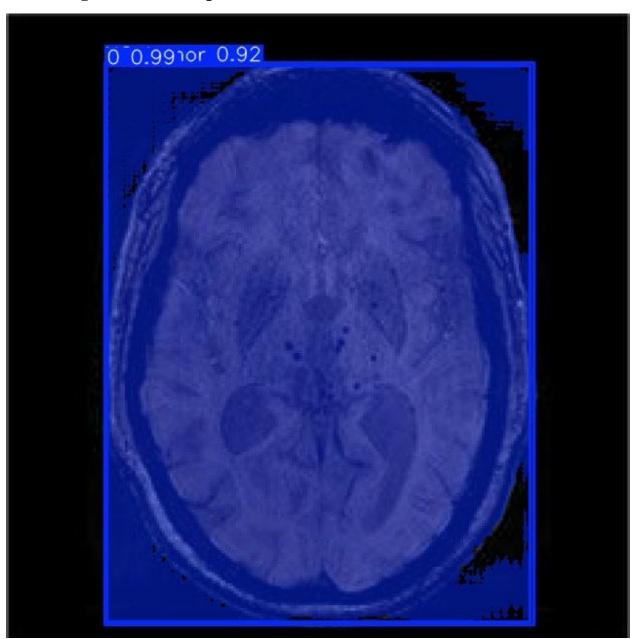


**Yolov11 Detection Output:** 





# **SAM2 Segmentation Output:**



#### **Code with Explanation:**

These lines import the YOLOv11 and SAM2 libraries from Ultralytics, which we will use for detection and segmentation.

- **♦** This **trains the model** using your dataset.
  - data points to the YAML file (it tells where images and labels are).
  - epochs=50 means training will run for 50 rounds.
  - imgsz=640 is the image size.
  - batch=8 is how many images are processed at once.
  - device="cpu" runs on CPU. Use "0" for GPU.

YOLO(...): Loads the trained model from the path to best.pt (this is the best model saved during training).

source="test\_images/": Path to the folder where your test images are saved.

save=True: Saves the output (with bounding boxes) in a new folder (usually runs/detect/predict).

device="cpu": Ensures the model runs on your CPU. (Use "0" if you have a GPU available.)

```
# Step 3: Load the SAM2 model (make sure sam b.pt is downloaded)
0
    sam model = SAM("sam b.pt")
1
2
    # Step 4: Loop through all YOLO results and segment using SAM2
.3
    for result in results:
4
        class ids = result.boxes.cls.int().tolist() # class ids of detections
.5
        if len(class ids): # if detection exists
6
            boxes = result.boxes.xyxy # get bounding boxes
7
            sam_model(
8.
                image=result.orig_img,  # original input image
9
                                            # detected bounding boxes from YOLO
0
                bboxes=boxes,
                verbose=False,
11
2
                save=True,
13
                device='cpu'
                                           # use CPU
```

The code loads the trained YOLO model to detect tumors in multiple images. For each detected tumor, it extracts the bounding box and passes it along with the original image to the SAM2 model. SAM2 then performs precise segmentation inside those boxes, and the segmented results are saved. The code runs on the CPU to ensure compatibility.

#### **Task 2:**

#### **Chapter 1: Definitions and Types of Machine Learning**

#### 1. Machine Learning (ML)

Machine Learning is a field of computer science that enables systems to learn patterns from data and make decisions or predictions without being explicitly programmed. It focuses on developing models that improve over time with experience.

### 2. Supervised Learning

Supervised Learning involves training a model on labeled data, where the input comes with the correct output. The goal is to learn a function that maps inputs to desired outputs.

**Example**: Predicting house prices based on historical data.

### 3. Unsupervised Learning

Unsupervised Learning works with data that has no labels. The goal is to find hidden patterns or groupings in the data.

**Example**: Clustering customers based on purchasing behavior.

### 4. Semi-Supervised Learning

This method combines a small amount of labeled data with a large amount of unlabeled data. It helps improve learning accuracy when labeling is costly or time-consuming.

**Example**: Training a model with a few labeled medical images and many unlabeled ones.

#### 5. Reinforcement Learning

An agent learns by interacting with an environment, receiving rewards or penalties based on its actions. It's commonly used in robotics, gaming, and autonomous driving.

**Example**: Training an AI to play chess or control a robot.

## **M** Comparison Tables

### **★** Supervised vs Unsupervised Learning

Feature Supervised Learning Unsupervised Learning

Data Type Labeled data

Unlabeled data

Goal Predict outcome/labels Find structure/patterns

Examples Regression, Classification Clustering, Dimensionality Reduction

Output Predicts labels Groups or features

Difficulty Easier to evaluate Harder to evaluate objectively

### **\*** Batch vs Online Learning

Feature Batch Learning Online Learning

Data Processing All at once (offline)

Incrementally (streaming)

Speed Slower, resource-intensive Fast and scalable

Use Case Stable datasets Dynamic data (e.g., stock market)

Retraining Needs complete retraining Learns from new data on the fly

#### ☐ Chapter 2: Code Implementation with Output

Below are the **steps and code blocks** from Chapter 2 (End-to-End ML Project). Each block includes an explanation.

#### **Step 1: Load Dataset**

```
from sklearn.datasets import fetch_california_housing
housing = fetch_california_housing(as_frame=True)
df = housing.frame
df.head()
```

#### **Step 2: Train-Test Split**

```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(df, test_size=0.2, random_state=42)
```

#### **Step 3: Data Exploration**

```
import matplotlib.pyplot as plt
df.hist(bins=50, figsize=(20,15))
plt.show()
```

### **Step 4: Correlation Matrix**

```
corr_matrix = df.corr()
corr_matrix["MedHouseVal"].sort_values(ascending=False)
```

### **Step 5: Feature Engineering**

```
df['rooms_per_household'] = df['AveRooms'] / df['Households'
df['bedrooms_per_room'] = df['AveBedrms'] / df['AveRooms']
```

### **Step 6: Handling Missing Values**

```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
df_num = df.drop("MedHouseVal", axis=1)
imputer.fit(df_num)
X = imputer.transform(df_num)
```

### **Step 7: Feature Scaling with Pipeline**

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median"))
        ('std_scaler', StandardScaler()),
])

df_prepared = pipeline.fit_transform(df_num)
```

### **Step 8: Training a Linear Model**

```
from sklearn.linear_model import LinearRegression
lin_reg = LinearRegression()
lin_reg.fit(df_prepared, df["MedHouseVal"])
```