# Mushroom classification

## MLOps Project Report

(Side note: I'm sorry if I went a little overboard with the project and the documentation…. I had a bit too much fun adding stuff once I got the hang of it.)

## Table of Contents

# 1. Introduction

This report outlines the details of my MLOps project of mushroom classification. The project's primary objective is to demonstrate the principles of MLOps by building an end-to-end pipeline for creating, training, deploying, and testing a machine learning model using **Azure Machine Learning (Azure ML)** services. The report highlights key aspects of the project, including data preparation, model training and evaluation, deployment with FastAPI, integration possibilities, and automation strategies.

Look at demo videos

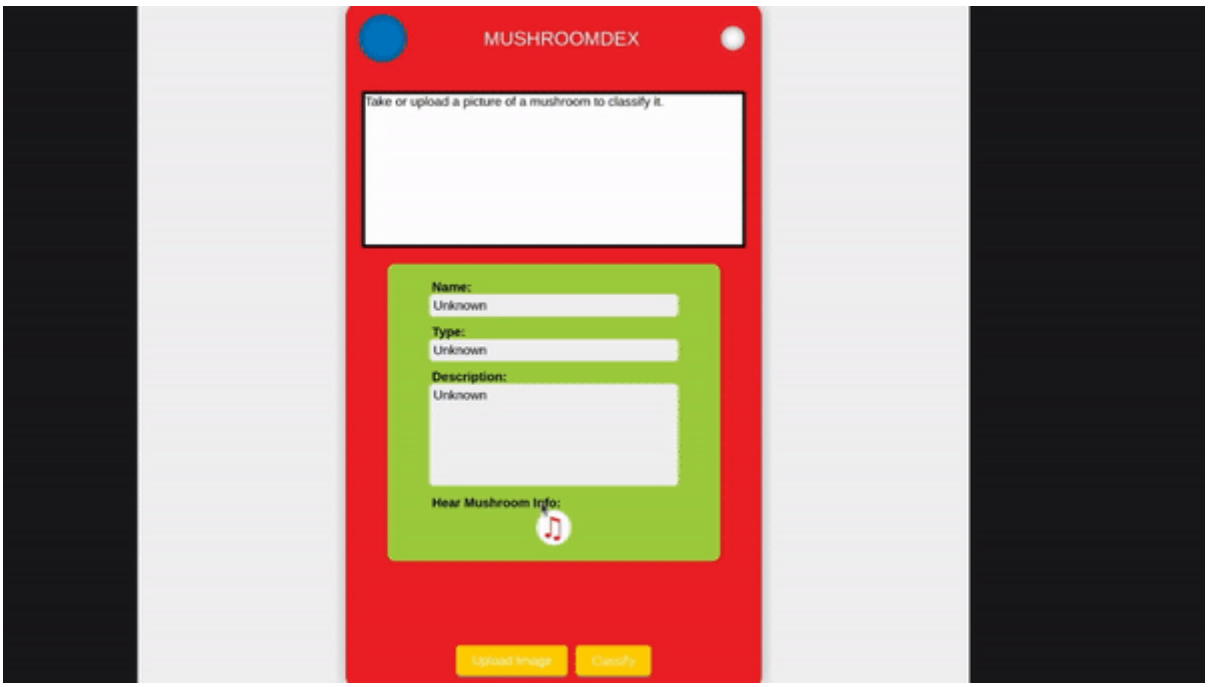



Figure 1: webapp

# 2. Project Overview

## 2.1 Dataset

The project involves the classification of mushrooms into nine distinct categories. The dataset used for this task contains of 6000+ images of 9 different mushroom families, each separated in its own folder.

The dataset I used: Mushroom Classification Dataset on Kaggle

# Mushroom Classification Dataset

Image Classification

Data Card | Code (4) | Discussion (2)

## About Dataset

**This dataset is used to classify 9 kinds of mushroom.**
**If you like this dataset and find it useful, please give a thumbs up 👍👍👍👍**
**🍄🍄🍄🍄🍄**
**Pay attention that there are some truncated images in this dataset(maybe only one, I'm not sure), so you are not recommended to use function like ImageFolder to load the whole dataset.**
**Otherwise, you will get OS Error, which I have shown you in my notebook. It's better to rewrite Dataset class.**

**Usability**
7.50

**License**
Community Data License Agree...

**Expected update frequency**
Never

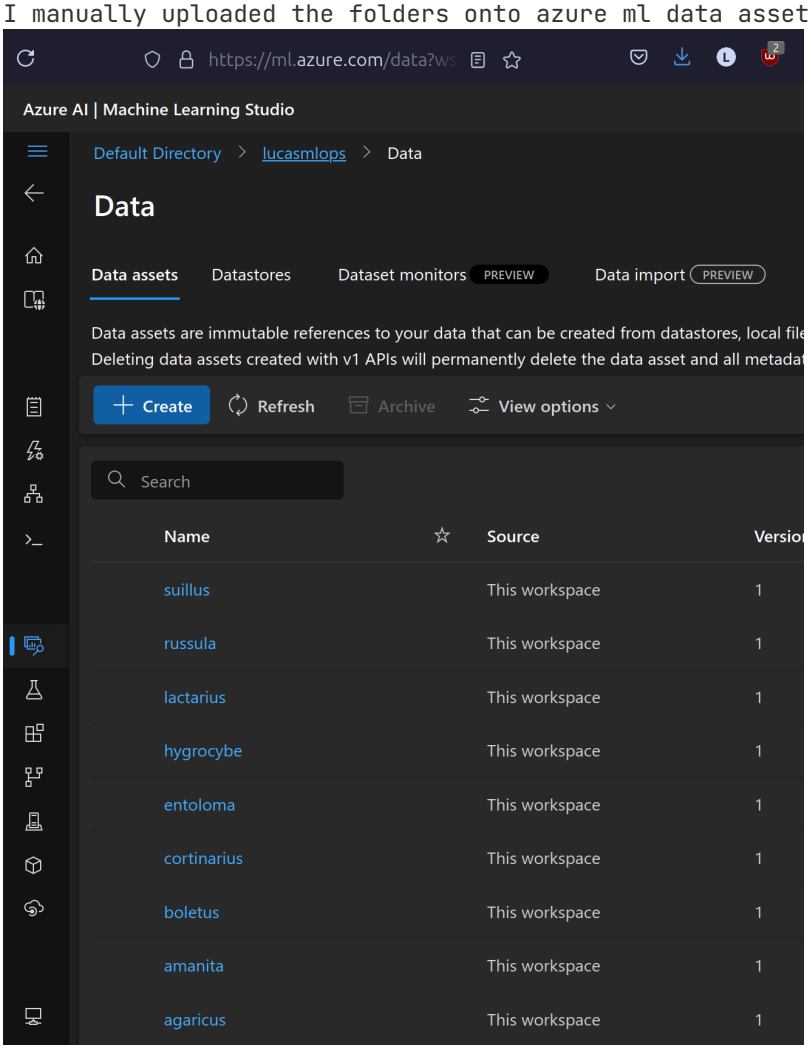
**Tags**
Online Communities
Biology | Computer Vision
Image Classification

Figure 2: dataset

The dataset contains images like this:

### 2.1.1 Data upload

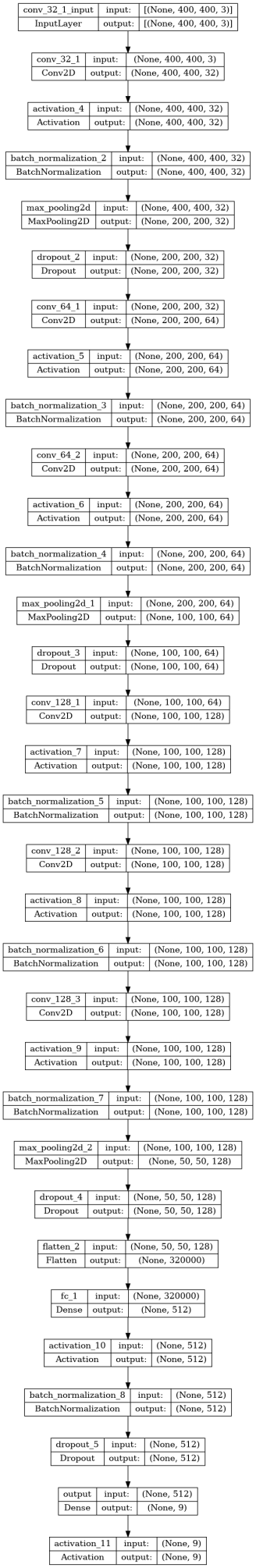
I manually uploaded the folders onto azure ml data assets for this project.




## 2.2 AI Model Selection: VGG19 with Transfer Learning

The chosen model for this mushroom classification project is based on the VGG19 architecture with transfer learning.

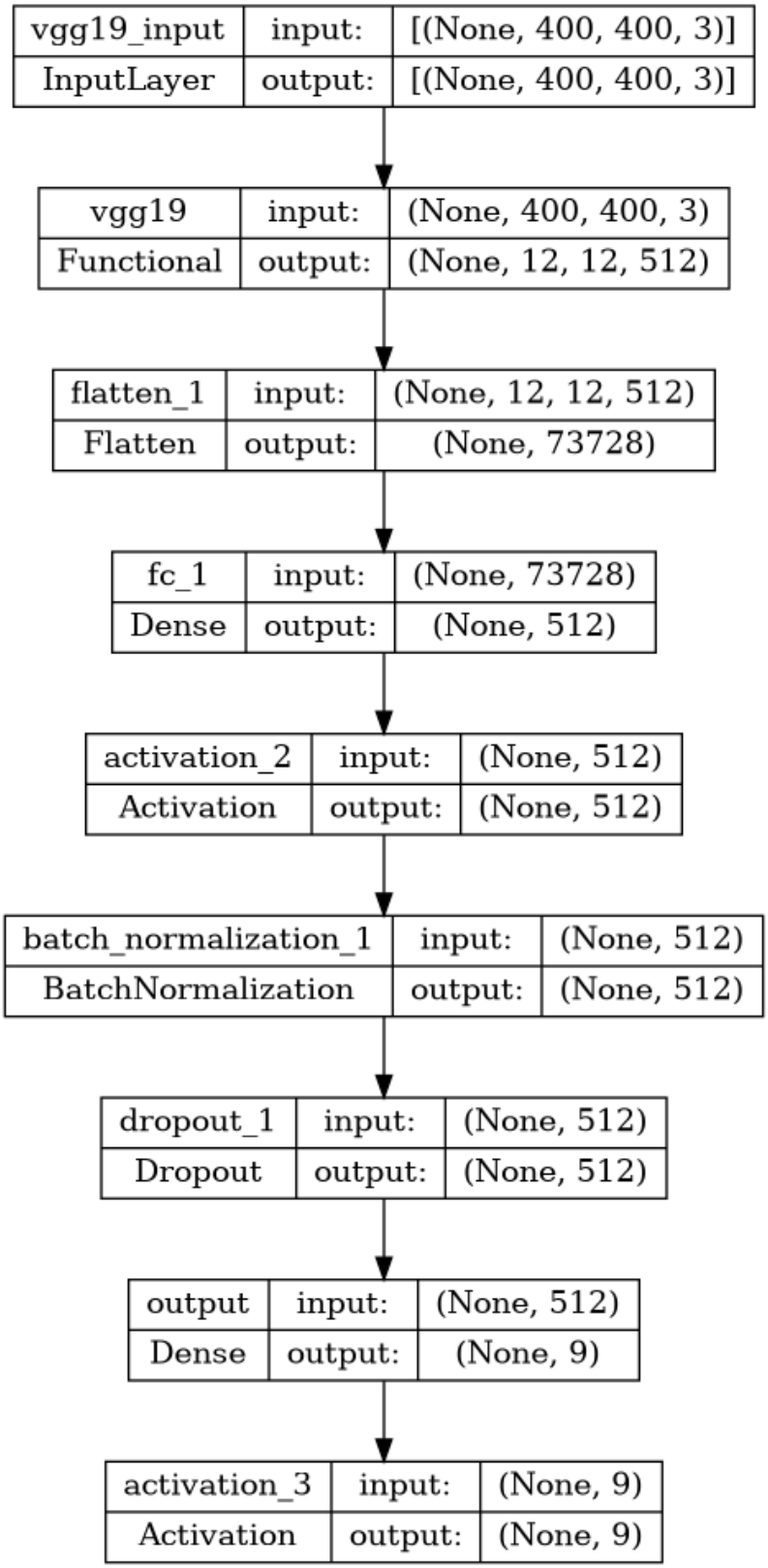
## 2.2.1 Model decision



Results with a custom CNN

```
              precision    recall  f1-score   support

           0       0.20      0.03      0.05        71
           1       0.62      0.10      0.17       150
           2       0.46      0.67      0.55       215
           3       0.31      0.10      0.15       168
           4       0.38      0.04      0.07        73
           5       0.50      0.05      0.09        64
           6       0.34      0.73      0.46       313
           7       0.31      0.33      0.32       151
           8       0.08      0.02      0.03        63

    accuracy                           0.37      1268
   macro avg       0.35      0.23      0.21      1268
weighted avg       0.37      0.37      0.30      1268

[[  2   1   5   1   0   1  50  11   0]
 [  2  15  38   5   0   1  53  35   1]
 [  0   0 144   3   0   1  52  13   2]
 [  1   1  32  16   0   0 100  15   3]
 [  1   1   5   6   3   0  49   7   1]
 [  0   3  22   3   0   3  25   6   2]
 [  4   3  33  13   5   0 230  22   3]
 [  0   0  14   1   0   0  86  50   0]
 [  0   0  19   4   0   0  36   3   1]]
DONE TRAINING
```

Model architecture with Transfer learning (VGG19 imagenet)


vgg19_input | input: | [(None, 400, 400, 3)]
InputLayer | output: | [(None, 400, 400, 3)]
vgg19 | input: | (None, 400, 400, 3)
Functional | output: | (None, 12, 12, 512)
flatten_1 | input: | (None, 12, 12, 512)
Flatten | output: | (None, 73728)
fc_1 | input: | (None, 73728)
Dense | output: | (None, 512)
activation_2 | input: | (None, 512)
Activation | output: | (None, 512)
batch_normalization_1 | input: | (None, 512)
BatchNormalization | output: | (None, 512)
dropout_1 | input: | (None, 512)
Dropout | output: | (None, 512)
output | input: | (None, 512)
Dense | output: | (None, 9)
activation_3 | input: | (None, 9)
Activation | output: | (None, 9)

Results with transfer learning (VGG19)

```
              precision    recall  f1-score   support

           0       0.51      0.55      0.53        71
           1       0.79      0.81      0.80       150
           2       0.79      0.90      0.84       215
           3       0.72      0.66      0.69       168
           4       0.71      0.53      0.61        73
           5       0.70      0.66      0.68        64
           6       0.72      0.71      0.71       313
           7       0.61      0.66      0.63       151
           8       0.73      0.57      0.64        63

    accuracy                           0.71      1268
   macro avg       0.70      0.67      0.68      1268
weighted avg       0.71      0.71      0.71      1268

[[ 39   7   4   1   2   0  12   5   1]
 [  7 122   6   2   0   0   5   8   0]
 [  2   4 193   3   1   0   7   2   3]
 [  5   6  10 111   6   3  16   7   4]
 [  3   1   2   5  39   7   8   8   0]
 [  0   1   1   7   3  42   4   6   0]
 [ 13   7  11  18   4   4 223  28   5]
 [  5   4   7   2   0   4  30  99   0]
 [  2   2  11   6   0   0   6   0  36]]
```

The transfer learning model had better accuracy and recall on all the different classes, so I decided to use that one.

## 2.3 Data Preprocessing: Steps for Optimal Dataset Preparation

Effective data preprocessing is a really important step in machine learning projects, ensuring that the dataset is ready for model training. Here are the steps I took to prepare the data:

### 2.3.1 Data preparation for this specific dataset (done outside of the pipeline)

```python
# assuming the dataset is in the ./Mushrooms directory
#for ./Mushrooms/Agaricus rename all images to their 'className + _ + number.jpg'
import os
import sys
import shutil

path = './Mushrooms/'
for x in sorted(os.listdir(path)):
    print(x)
    index_y = 0
    for y in sorted(os.listdir(path + x)):
        #split y on _ and take the second part
        name = y.split('_')[1]
        nr = y.split('_')[0]
        #remove .jpg
        name = name.split('.')[0]
        #add class name
        name = x+'_'+nr+'.jpg'
```

```
        #rename
        os.rename(path+x+'/'+y, path+x+'/'+name)
```

### 2.3.2 Data prep before training

this resizes the images to 400x400, and saves them in the output directory.

```
    output_dir = args.output_data
    size = (400, 400) # Later we can also pass this as a property
    for file in glob(args.data + "/*.jpg"):
        try:
            img = Image.open(file)
            img_resized = img.resize(size)
            # Save the resized image with the new name to the output directory
            output_file = os.path.join(output_dir,os.path.basename(file))
            img_resized.save(output_file)
        except OSError as e:
            print(f"Error processing {file}: {e}")
```

then there is traintestsplit.py, this just takes some images and puts them in a training_folder and test_folder. this is really basic so I wont go into detail here.

### 2.3.3 Target Label Extraction

This function extracts the mushroom category (label) from the file paths, providing the ground truth labels for each image.

```
    def getTargets(filepaths: List[str]) -> List[str]:
     labels = [fp.split('/')[-1].split('_')[0] for fp in filepaths]
     return labels
```

### 2.3.4 Label Encoding

The LabelEncoder maps each unique mushroom category to a numerical value and then converts these numerical labels into one-hot encoded vectors, which are compatible with machine learning models.

```
    def encodeLabels(y_train: List, y_test: List):
        label_encoder = LabelEncoder()
        y_train_labels = label_encoder.fit_transform(y_train)
        y_test_labels = label_encoder.transform(y_test)
        # Convert the labels to one-hot encoded vectors
        y_train_1h = to_categorical(y_train_labels)
        y_test_1h = to_categorical(y_test_labels)
        # Get the list of unique labels
        LABELS = label_encoder.classes_
        print(f"{LABELS} -- {label_encoder.transform(LABELS)}")
        # Return the encoded labels
        return LABELS, y_train_1h, y_test_1h
```

### 2.3.5 Feature Extraction

This function reads and converts the images into numerical arrays (pixel values), preparing them for training.

```
    def getFeatures(filepaths: List[str]) -> np.array:
     images = []
     for imagePath in filepaths:
         image = Image.open(imagePath).convert("RGB")
         image = np.array(image)
         images.append(image)
     return np.array(images)
```

# Prerequisites

Before continuing, ensure you have the following prerequisites set up

## Azure Credentials

Azure subscription with necessary permissions to create and manage Azure ML resources. Service principal with contributor access to the Azure subscription.

Create a service principal auth token with the Azure CLI:

```
az ad sp create-for-rbac --name "<NAME>" --role contributor --scopes /subscriptions/<SUBSCRIPTION_ID>
↪  --json-auth
```

It will look something like this:

```
{
    "clientId": "<CLIENT_ID>",
    "clientSecret": "<CLIENT_SECRET>",
    "subscriptionId": "<SUBSCRIPTION_ID>",
    "tenantId": "<TENANT_ID>"
}
```

## GitHub Secrets

The following secrets need to be configured in your GitHub repository for the pipelines to authenticate and interact with Azure resources:

```
AZURE_CREDENTIALS: A JSON string containing your Azure service principal details. This is used for
↪  authenticating with Azure from GitHub Actions. ( we created this in the previous step)

DOCKER_HUB_PASSWORD: Your Docker Hub password or access token if you're pushing images to Docker Hub.

repo_token: A GitHub token with necessary permissions for actions such as pushing container images to GitHub
↪  Container Registry.
```

### Getting Started

> !!! Make sure you have the necessary permissions and configurations set up in your Azure ML workspace and github repository. !!!

You will need to go into the pipelines folder and change what you need for your specific use case, adding your own image/data paths.

Same thing with the components folder, you will need to adjust the model and the preprocessing that I just went over to your specific use case.

# 3. Cloud AI Services

Azure Machine Learning Service was utilized extensively throughout the project. Azure ML provided a powerful platform for managing the entire MLOps pipeline, from data preparation to model registration. (It took a while to get used to working with azure ml, but once I got the hang of it, it was nice to see all the possibilities it offers)

## 3.1 Compute Resource Management

Compute resources were created and managed within Azure ML. This included setting up an Azure ML compute cluster instead of a compute instance to make the training faster (more nodes) since I had to preprocess 9 imagesets into a train/test split.

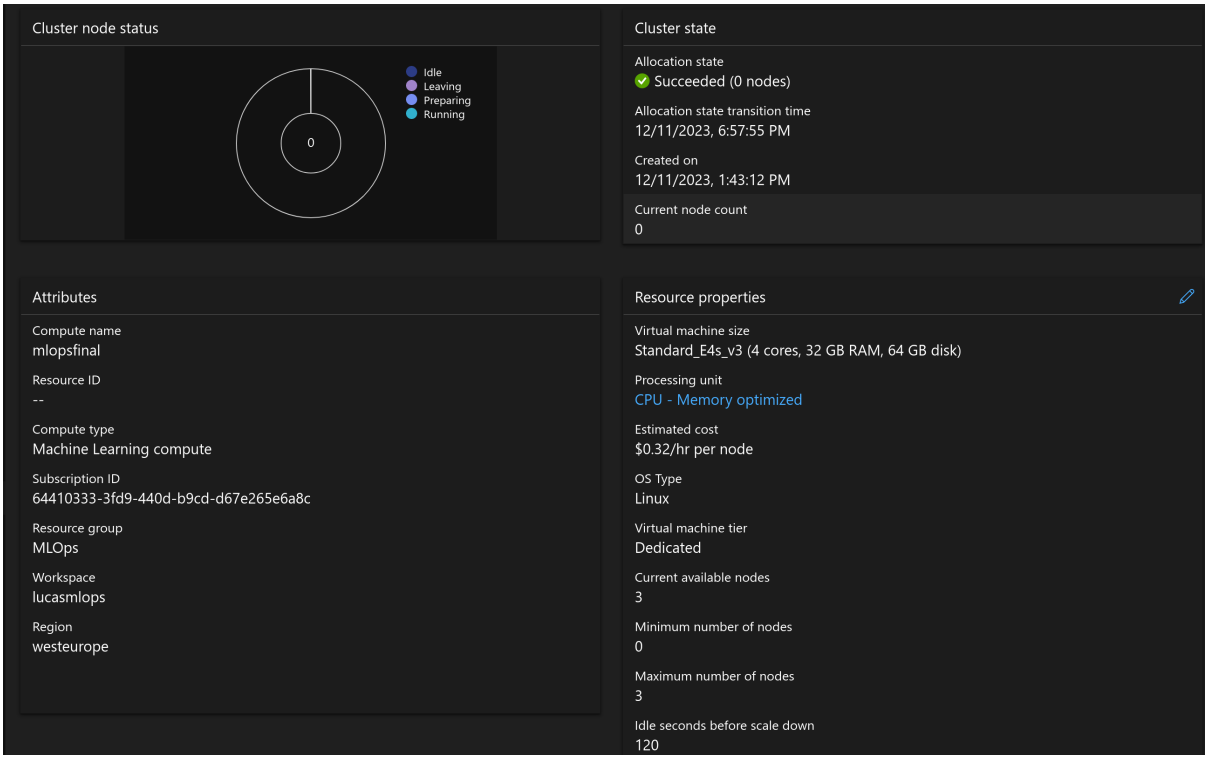



Figure 3: compute_cluster

Make sure to change the compute cluster to your own needs, this is what I used (found in ./environments/compute.yaml):


Figure 4: compute_cluster

## 3.2 Environment Setup

Azure ML enabled the creation and management of environments for the project. Specifically, environment configurations for libraries like Pillow and TensorFlow that were defined in separate YAML files, found in the ./environments directory.

Create the environments with this command:

```
az ml environment create --file my_env.yml --resource-group my-resource-group --workspace-name my-workspace
```

Where file is either these files:

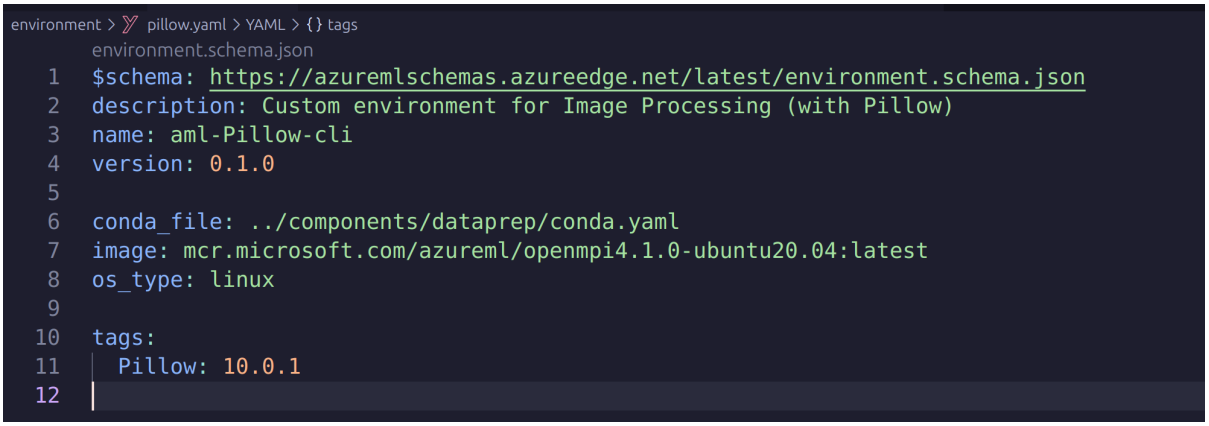



Figure 5: pillow

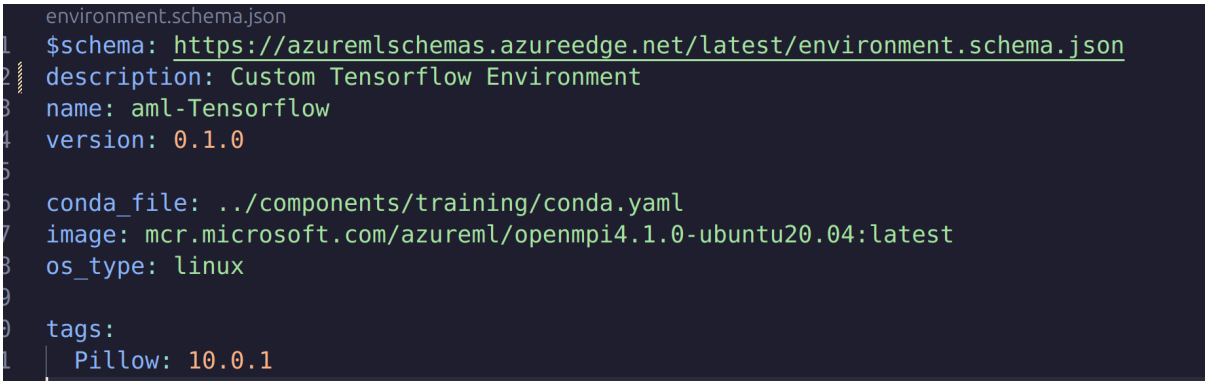


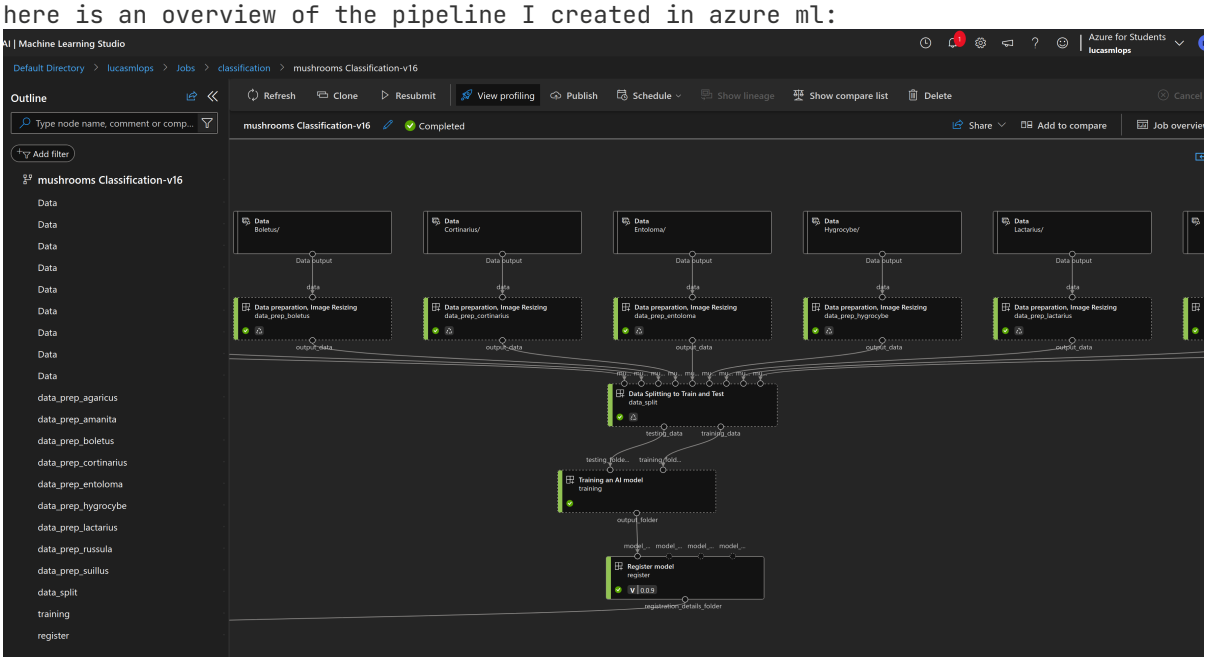

Figure 6: tensorflow

# 4. Model Training and Evaluation

This section outlines the steps involved in training and evaluating the machine learning model.

## 4.1 Azure ML

here is an overview of the pipeline I created in azure ml:




## 4.2 Model Training

This is the 'main' component of training my model, here the model is build, compiled and trained.

```
    ## since the training time is already large the amount of epochs is kept really low (5 in this case)
    INITIAL_LEARNING_RATE = 0.01
    BATCH_SIZE = 32
    PATIENCE = 11
    model_name = 'mushroom-cnn'

    opt = tf.keras.optimizers.legacy.SGD(lr=INITIAL_LEARNING_RATE, decay=INITIAL_LEARNING_RATE / MAX_EPOCHS) #
    ↪  Define the Optimizer

    model = buildModel((400, 400, 3), 9) # Create the AI model as defined in the utils script.

    #compile the model
    model.compile(loss="categorical_crossentropy", optimizer=opt, metrics=["accuracy"])

    #data augmentation
    aug = ImageDataGenerator(rotation_range=30, width_shift_range=0.1,
                             height_shift_range=0.1, shear_range=0.2, zoom_range=0.2,
                             horizontal_flip=True, fill_mode="nearest")


```

```
    # train the network
    history = model.fit( aug.flow(X_train, y_train, batch_size=BATCH_SIZE),
                         validation_data=(X_test, y_test),
                         steps_per_epoch=len(X_train) // BATCH_SIZE,
                         epochs=MAX_EPOCHS,
                         callbacks=[cb_save_best_model, cb_early_stop, cb_reduce_lr_on_plateau] )
```

## 4.3 Model Evaluation

The performance of the trained model was evaluated using various metrics, including accuracy, precision, recall, and F1-score and a confusion matrix.

```
              precision    recall  f1-score   support

           0       0.51      0.55      0.53        71
           1       0.79      0.81      0.80       150
           2       0.79      0.90      0.84       215
           3       0.72      0.66      0.69       168
           4       0.71      0.53      0.61        73
           5       0.70      0.66      0.68        64
           6       0.72      0.71      0.71       313
           7       0.61      0.66      0.63       151
           8       0.73      0.57      0.64        63

    accuracy                           0.71      1268
   macro avg       0.70      0.67      0.68      1268
weighted avg       0.71      0.71      0.71      1268

[[ 39   7   4   1   2   0  12   5   1]
 [  7 122   6   2   0   0   5   8   0]
 [  2   4 193   3   1   0   7   2   3]
 [  5   6  10 111   6   3  16   7   4]
 [  3   1   2   5  39   7   8   8   0]
 [  0   1   1   7   3  42   4   6   0]
 [ 13   7  11  18   4   4 223  28   5]
 [  5   4   7   2   0   4  30  99   0]
 [  2   2  11   6   0   0   6   0  36]]
```

Figure 7: metrics

### 4.3.1 conclusions

The model is performing pretty okay considering I only had around 259 images for 2 of the classes, my dataset wasnt balanced at all. (Adding data augmentation helped a lot with this)

And the training already took 5hours, so It wasn't really feasible to add more data in my case, given the time frame of this project (and limited money resources).

# 5. Deployment

We were tasked with deploying a fastapi. I also added a webapp and a gradio gui to create a more visual experience.

## 5.1 Fastapi Deployment

The trained model is integrated into a fastapi, which Is then build into a docker image and then finally that image is then pushed to my github packages repo.

I later use this docker image to deploy the api on kubernetes.

Dockerfile for the fastapi

```dockerfile
nference > dockerfile > ...
FROM python:3.10

WORKDIR /app

COPY requirements.txt .
RUN pip install -r requirements.txt

COPY ./ ./

# CMD ["python", "main.py"]
CMD ["uvicorn", "main:app", "--host", "0.0.0.0", "--port", "8000"]
```

Deployment and service file for the fastapi

```yaml
io.k8s.api.apps.v1.Deployment (v1@deployment.json)
apiVersion: apps/v1
kind: Deployment
metadata:
  name: api-deployment
spec:
  replicas: 1
  selector:
    matchLabels:
      app: api
  template:
    metadata:
      labels:
        app: api
    spec:
      containers:
        - name: api
          image: ghcr.io/driessenslucas/mlops-mushrooms-api:latest
          ports:
            - containerPort: 8000
          resources:
            requests:
              memory: '1Gi'
              cpu: '500m'
            limits:
              memory: '4Gi'
              cpu: '2'
```

```
io.k8s.api.core.v1.Service (v1@service.json)
# service.yaml
apiVersion: v1
kind: Service
metadata:
  name: api-service
spec:
  selector:
    app: api
  ports:
    - protocol: TCP
      port: 80
      targetPort: 8000
  type: NodePort
```

## 5.3 API Endpoints

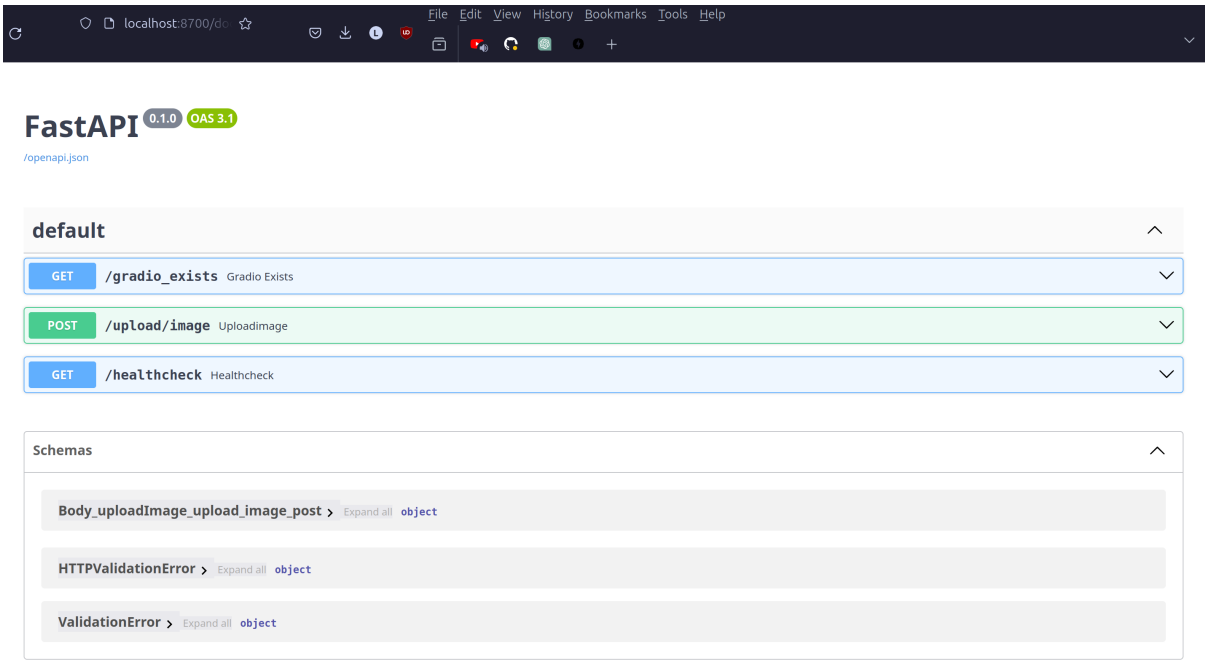



Figure 8: fastapi

## 5.4 Web App

This simple web app creates a fun and interactive way to test the finished product, its made to do an api request with an uploaded image, based on the result it will display some information about the mushroom. (I added text to speech to spice it up a bit)

Look at the code snippet below to see how the api call is done.

```
classifyButton.addEventListener('click', function () {
    //get image data from canvas
    const imageDataURL = document.getElementById('mushroomImage').src;
    //send image data to api
```

```
    fetch(imageDataURL)
        .then((res) => res.blob())
        .then((blob) => {
            // Create a FormData object
            const formData = new FormData();
            formData.append('img', blob, 'image.png');

            // Send the image file to the FastAPI server
            fetch('http://api-service/upload/image', {
                method: 'POST',
                body: formData,
            })
                .then((response) => response.json())
                .then((mushroomFamily) => {
                    console.log(mushroomFamily);

                    // Update the UI with the received data
                    mushroomName.textContent = mushroomFamily || 'Unknown';
                    mushroomType.textContent = 'Mushroom Family';
                    mushroomDescription.textContent =
                        mushroomDescriptions.find((x) => x.name === mushroomFamily)
                            .description || 'No description available';

                    //make sound button available
                    soundButton.style.display = 'block';
                })
                .catch((error) => {
                    console.error('Error:', error);
                });
        });
});
```

Dockerfile for the web app

web > dockerfile > ...

```
# Use the Nginx image from Docker Hub
FROM nginx:alpine

# Copy the static website files into the default Nginx public folder
COPY ./voice-overs/ /usr/share/nginx/html/voice-overs/
COPY index.html /usr/share/nginx/html/
COPY styles.css /usr/share/nginx/html/
COPY script.js /usr/share/nginx/html/

# Expose port 80
EXPOSE 80

# Start Nginx when the container has provisioned
CMD ["nginx", "-g", "daemon off;"]

```

Deployment and service for the web app on kubernetes

io.k8s.api.apps.v1.Deployment (v1@deployment.json)

```yaml
apiVersion: apps/v1
kind: Deployment
metadata:
  name: website-deployment
spec:
  replicas: 1
  selector:
    matchLabels:
      app: website
  template:
    metadata:
      labels:
        app: website
    spec:
      containers:
        - name: website
          image: ghcr.io/driessenslucas/mlops-mushrooms-website:latest
          imagePullPolicy: Always
          ports:
            - containerPort: 80
          resources:
            requests:
              memory: '2Gi'
              cpu: '500m'
            limits:
              memory: '4Gi'
              cpu: '2'
```

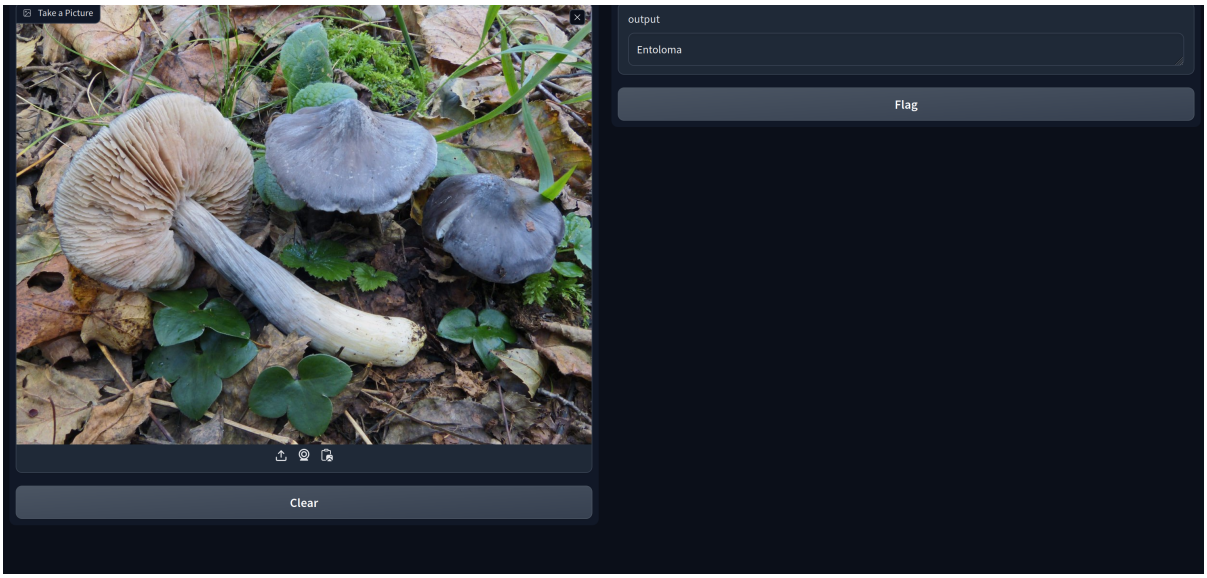
io.k8s.api.core.v1.Service (v1@service.json)

```yaml
apiVersion: v1
kind: Service
metadata:
  name: web-service
spec:
  selector:
    app: website
  ports:
    - protocol: TCP
      port: 80
      targetPort: 80
  type: NodePort
```

## 5.6 Gradio

I also used Gradio to build a simpler gui, since the webapp was made more for fun and as a potential software integration.

This was inplemented in the fastapi app (which wasn't easy to do…. Once the api starts, there will be an endpoint at /gradio, which will then show the gradio interface.)




```python
async def gradio():
    # implement gradio
    with gr.Blocks() as demo:
        # Function to make predictions using the loaded model
        def predict(image):
            original_image = image
            original_image = original_image.resize((400, 400))
            images_to_predict = np.expand_dims(np.array(original_image), axis=0)
            predictions = model.predict(images_to_predict)
            #get the highest probability
            classifications = predictions.argmax(axis=1)
            # Print probability of all classes
            print(predictions)
            #get the name of the mushroom after the prediction
            return f'{Mushrooms[classifications.tolist()[0]]}'
        # Gradio Interface for Mushroom Prediction
        iface = gr.Interface(
            fn=predict,
            inputs=gr.Image(type='pil', label='Take a Picture'),
            outputs='text',
            live=True
        )
    # Run Gradio Interface in the background
    global app
    demo.queue()
    demo.startup_events()
    app = gr.mount_gradio_app(app, demo, '/gradio')
```

## 5.7 Deployment on azure kubernetes !!! (bonus)

> This step was in my eyes the whole point of this assignment, creating a full pipeline from data to webapp, that is fully automated and deployed on a kubernetes cluster

Kubernetes Cluster Setup

**note:this has been barely tested since I'm limited in public ip's that azure will give me**

As I wasn't sure if this was part of the assignment, I added this as a bonus, I deployed the api and the website on azure kubernetes (instead of on my own machine), this was done by adjusting the github actions file.

For this I changed my strategy a bit, I changed from working with a clusterIP + port forwarding to a loadbalancer, this way I could set up an external ip in azure and access the api and website from anywhere (I should probably added some type of auth, but since its only able to upload a picture, it should be fine).

I had to add some new env variables in the github actions file, for this to work (this is the full updated env section):

```
env:
  NAMESPACE: mushroomspace
  GROUP: MLOps
  CLUSTER: mushrooms
  WORKSPACE: lucasmlops
  LOCATION: westeurope
  # Allow to override for each run, in the workflow dispatch manual starts
  CREATE_COMPUTE: ${{ github.event.inputs.create_compute }}
  TRAIN_MODEL: ${{ github.event.inputs.train_model }}
  SKIP_TRAINING_PIPELINE: ${{ github.event.inputs.skip_training_pipeline }}
  DEPLOY_MODEL: ${{ github.event.inputs.deploy_model }}
  DOWNLOAD_MODEL: ${{ github.event.inputs.download_model }}
  DEPLOY_KUBERNETES: ${{ github.event.inputs.deploy_kubernetes }}
  CREATE_CLUSTER: ${{ github.event.inputs.create_cluster }}
```

I then added a new step in the azure-pipeline job:

```
  - name: Create Kubernetes cluster
  uses: azure/CLI@v1
  id: prepare-kubernetes-cluster
  if: ${{ inputs.create_cluster }}
  with:
    azcliversion: 2.53.0
    inlineScript: |
      az aks create -g $GROUP -n $CLUSTER --enable-managed-identity --node-count 1 --enable-addons
↪   --enable-msi-auth-for-monitoring --generate-ssh-keys
```

And also added a new job responsible for deploying the api and the website on the kubernetes cluster:

```
deploy-kubernetes:
  needs: deploy
  if: ${{ inputs.deploy_kubernetes }}
  runs-on: ubuntu-latest
  steps:
    - name: Check out repository
      uses: actions/checkout@v4

    - name: Azure Login
      uses: azure/login@v1
      with:
```

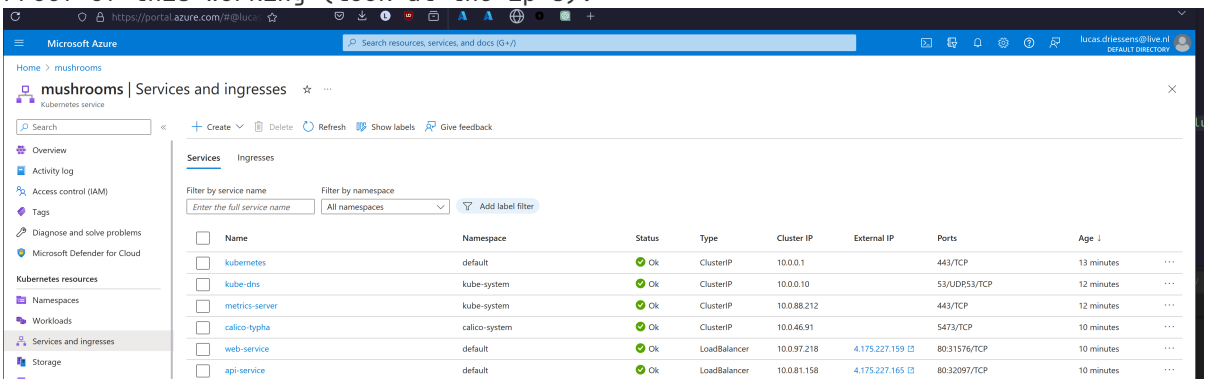
```
        creds: ${{ secrets.AZURE_CREDENTIALS }}

    - name: Set AKS context
      uses: azure/aks-set-context@v1
      with:
        creds: ${{ secrets.AZURE_CREDENTIALS }}
        cluster-name: ${{ env.CLUSTER }}
        resource-group: ${{ env.GROUP }}

    - name: Create Namespace or check namespace
      run: |
        kubectl create namespace $NAMESPACE || echo "namespace already exists"

    - name: deploy website and fastapi onto the kubernetes
      run: |
        kubectl apply -f ./web/deployment.yaml -n $NAMESPACE
        kubectl apply -f ./inference/deployment.yaml -n $NAMESPACE
```

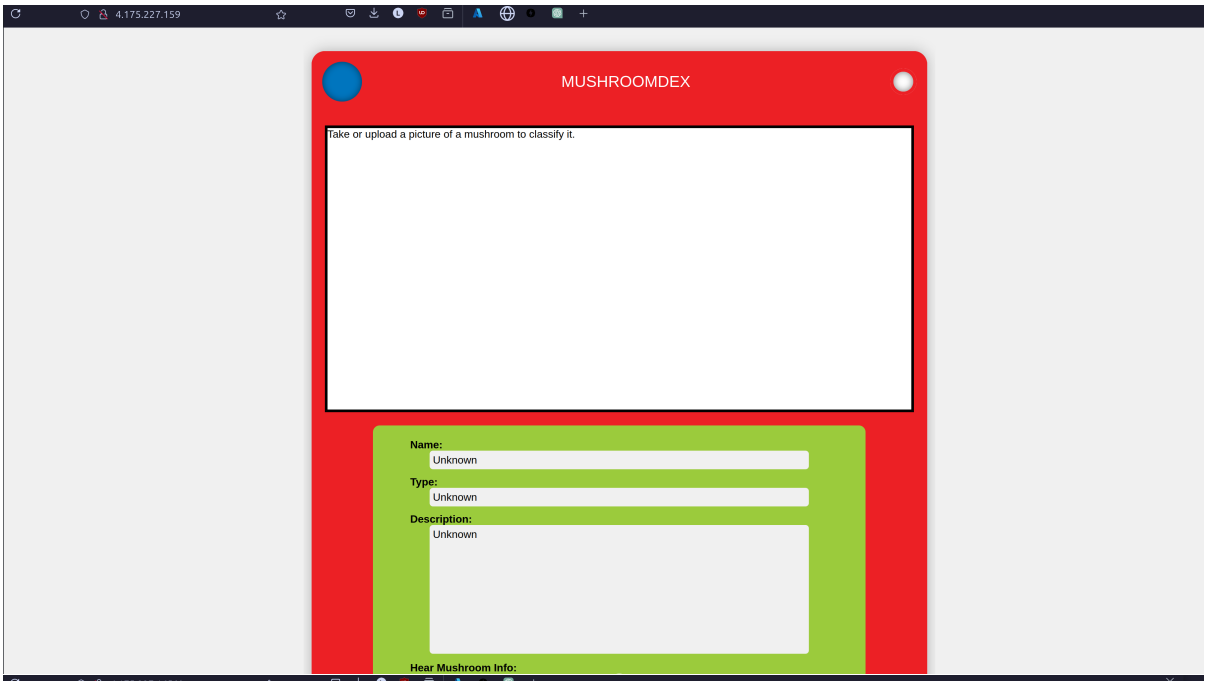
To ensure that the api and website are kept up-to-date I added a 'rolling-update' strategy to the deploy step (where the images get reuploaded to the github packages repo)

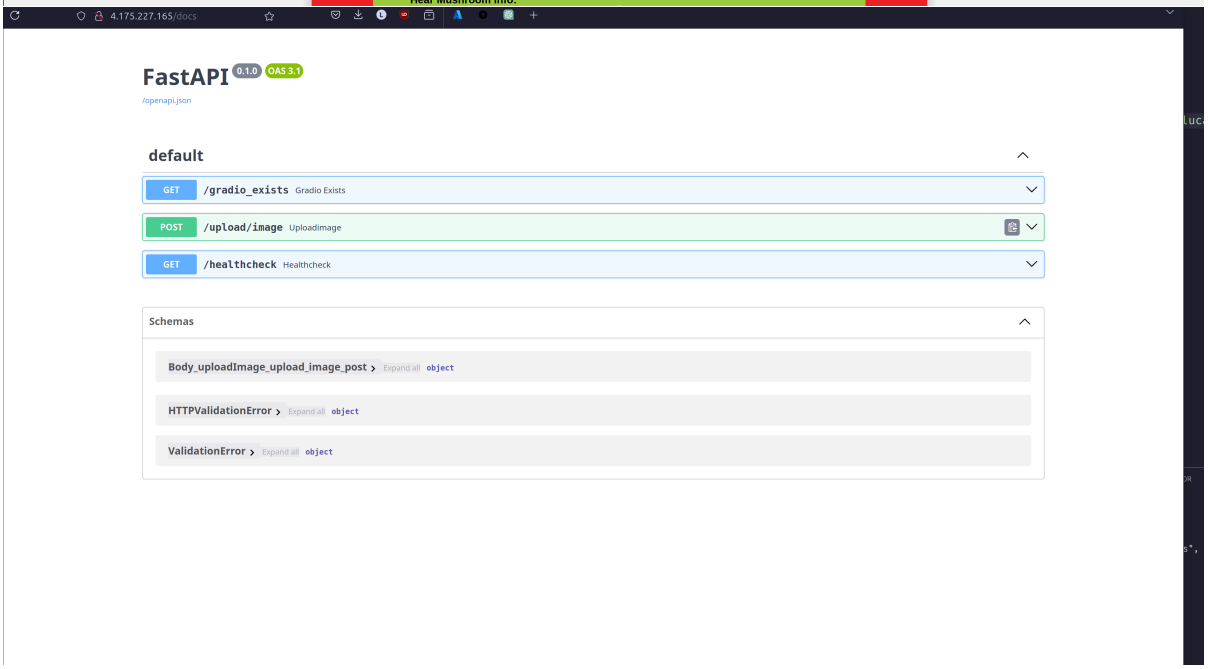
The deployment/*-deployment name is the metadata.name in the deployment.yaml files.

```
  - name: Update Kubernetes Deployment
  run: |
    kubectl set image deployment/api-deployment api=ghcr.io/driessenslucas/mlops-mushrooms-api:latest -n
↪   $NAMESPACE
    kubectl set image deployment/website-deployment
↪   website=ghcr.io/driessenslucas/mlops-mushrooms-website:latest -n $NAMESPACE
```

- Proof of this working (look at the ip's):

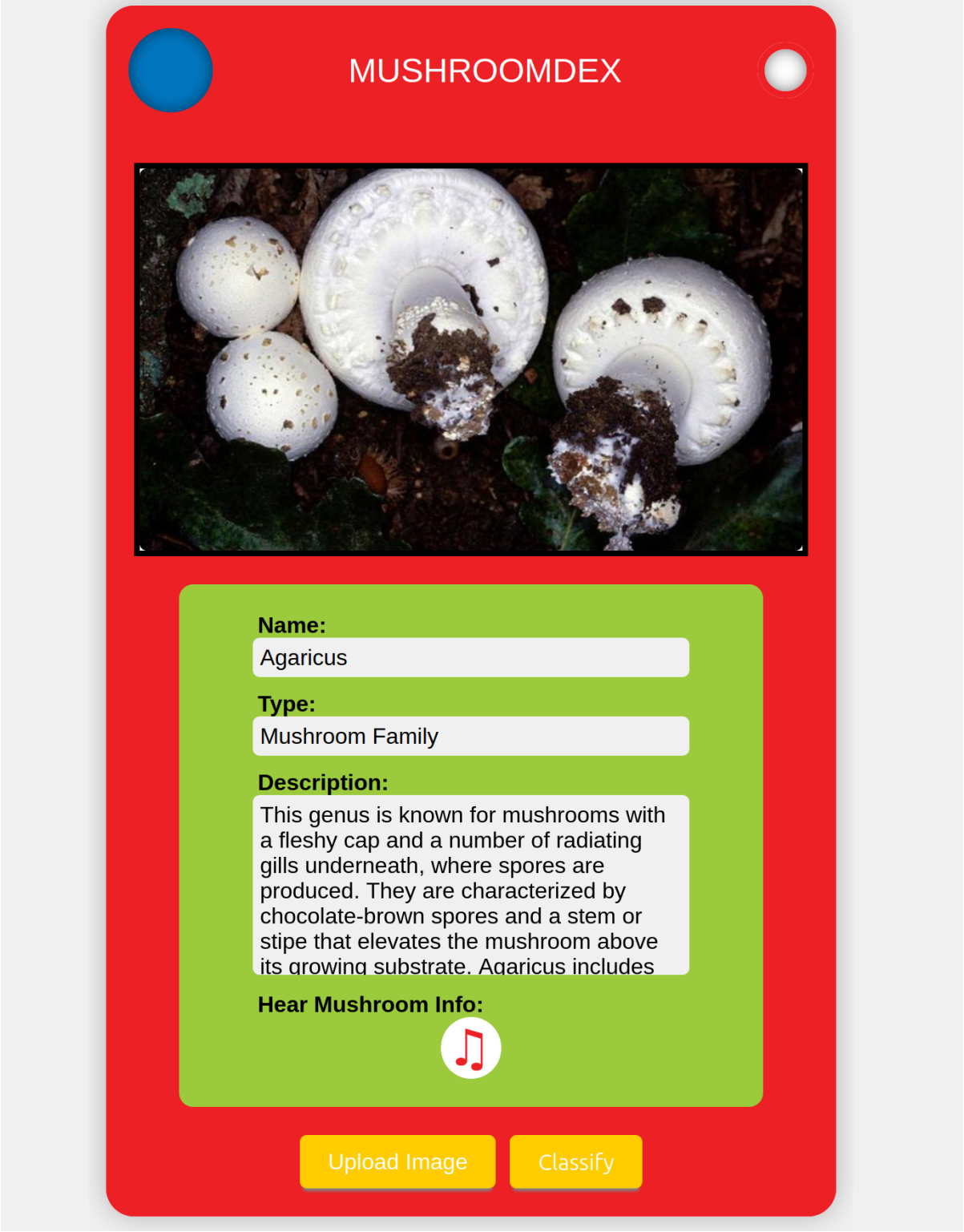



4.175.227.159
MUSHROOMDEX
Take or upload a picture of a mushroom to classify it.
Name:
Unknown
Type:
Unknown
Description:
Unknown
Hear Mushroom Info:


4.175.227.165/docs
FastAPI
0.1.0
OAS 3.1
/openapi.json
default
GET /gradio_exists Gradio Exists
POST /upload/image Uploadimage
GET /healthcheck Healthcheck
Schemas
Body_uploadImage_upload_image_post Expand all object
HTTPValidationError Expand all object
ValidationError Expand all object

# 6. Integration with Existing Software

In a practical scenario, this MLOps pipeline is ready to be integrated into an existing software system.




## 6.1 Fake company

As I didn't really have an actual fake company in mind, I created a webapp (as shown before) but this could be used in a lot of different ways, for example, a company that wants to classify mushrooms for their restaurant, or a company that wants to classify mushrooms for their mushroom farm, or a company that wants to classify mushrooms for their mushroom picking tours.

If there was a better more in depth dataset this could even be used to classify mushrooms in the wild, and help people identify mushrooms (to see if the are edible or not).

### 6.1.1 Integration in an existing software system

When you want to integrate this you just need to do an api call to the fastapi endpoints…. So there isnt much to it, you could deploy the api to a container app in azure for example. Or in a cloud kube cluster, like I did as a bonus.

# 7. Automation and Version Control

In this project I mainly used GitHub Actionsm which allows for the orchestration of various tasks, from data handling to model training and deployment, all triggered by specific GitHub events like code commits.

Automation and version control are found all over my MLOps pipeline. The key components of my automation strategy include:

```
Data Handling: Automating the extraction and preprocessing of data to prepare it for training.
Model Training: Triggering the training process of the machine learning model with specified parameters.
Model Evaluation: Systematically evaluating the model performance to ensure it meets our criteria.
Model Deployment: Deploying the model to my GitHub Packages repository for easy access.
Version Control: Using GitHub Actions to automate the version control of the model.
```

In the following sections, I delve into the specifics of each step, illustrating how GitHub Actions enhances our MLOps pipeline's efficiency and robustness.

## 7.1 GitHub Actions

I used github actions to automate the training and deployment of the model. The workflow is defined in the .github/workflows directory. It triggers a pipeline that goes the whole process of data extraction, preprocessing, training, evaluation, and deployment. each directory has its own yaml file for this.

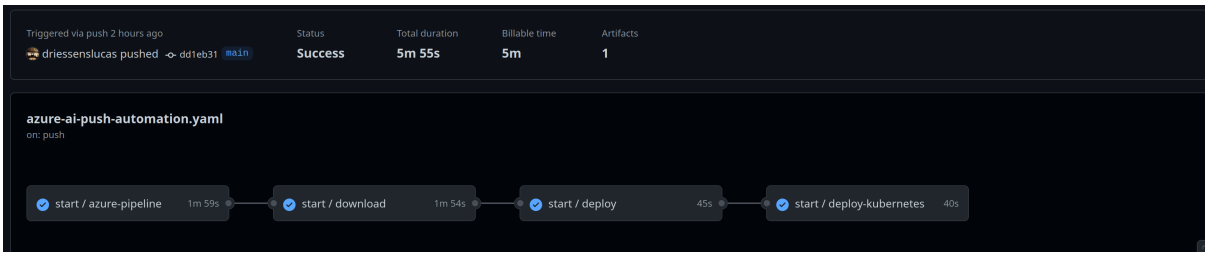
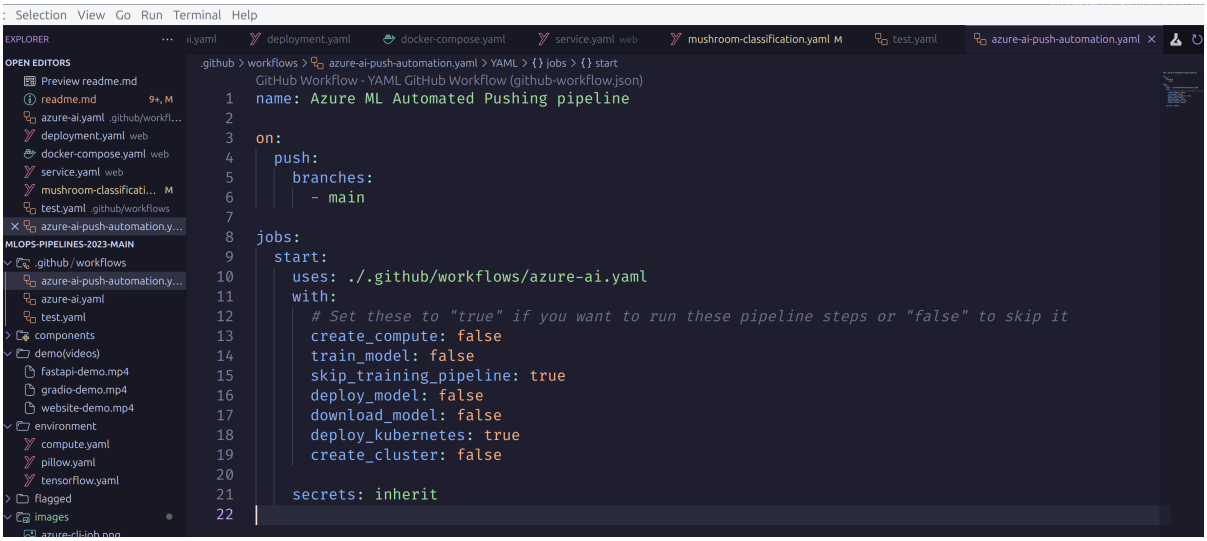



Figure 9: github actions

Pipeline start

Here you can set the environment variables for the pipeline, chosing if you want to create_compute, train_model, skip_training_pipeline, download_model or deploy_model these allow for a more flexible pipeline, where you can choose to skip certain steps. since you dont need to recreate the compute or train the model each time you want to redeploy it.




## Jobs

azure cli:

This job will login and create and/or start the compute cluster. and start the training pipeline if selected (./pipelines/mushroom-classification.yaml).

```yaml
jobs:
  azure-pipeline:
    if: ${{ inputs.skip_training_pipeline }}
    runs-on: ubuntu-latest
    # runs-on: self-hosted
    outputs:
      ai-model-version: ${{ steps.azure-ml-pipeline.outputs.latest_version }}
    steps:
      - name: Check out repository ...

      - name: Azure Login ...
      # AZURE_CREDENTIALS should be a secret in your repo containing a JSON string of your service principal

      - name: Install YQ ...

      - name: read-yaml-file ...

      - name: Create compute ...

      - name: Create Kubernetes cluster ...

      - name: Start compute ...

      - name: Execute Azure ML Script ...

      - name: Cleanup Compute ...
```

download model:

This will download the registred model from azure ml and save it in the ./inference directory on the created machine.

```yaml
  download:
    needs: azure-pipeline
    # Only run if azure-pipeline is succeeded OR skipped
    if: ${{ needs.azure-pipeline.result == 'success' || needs.azure-pipeline.result == 'skipped'  && i
    # runs-on: self-hosted
    runs-on: ubuntu-latest
    steps:
      - name: Check out repository ...

      - name: Azure Login ...

      - name: Set model version ...

      - name: Upload API Code for Docker ...
```

deploy model:

This will deploy the docker files to the github packages repo

```yaml
deploy:
  needs: download
  # Only run if download is succeeded OR skipped AND if the deploy_model variable is true
  if: ${{
    (
    needs.download.result == 'success' ||
    needs.download.result == 'skipped'
    ) &&
    inputs.deploy_model }}
  runs-on: self-hosted
  # runs-on: ubuntu-latest
  steps:
    - name: Gather Docker Meta Information …

    # Enter your GITHUB Token here!
    - name: Login to GHCR …

    - name: Download API Code for Docker …

    - name: Docker Build and push …

    - name: Docker build and push website image …

    - name: Update Kubernetes Deployment …
```

## All this can then be tested (locally) with the test.yaml file

Testing file:

(This will require a local github actions runner) This will deploy the api and the website on kuberenetes. It will create a new namespace and then port forward both the api and the website to the localhost, allowing the user to explore. After testing is done it removes the namespace and all the containing services.

```yaml
name: Test Local Runner

on:
  workflow_dispatch:
  push:
    branches:
      - main

jobs:
  default-job-test:
    runs-on: self-hosted

    steps:
      - name: Check out repository …

      - name: Set up Kubectl …

      - name: Clean up previous namespaces …

      - name: Create Test Namespace …

      - name: Deploy to Kubernetes for Testing …

      - name: Deploy Website to Kubernetes for Testing …

      - name: Get Deployment Pods and Wait for Them to Be Ready …

      - name: Execute Tests …

      - name: Cleanup …
```

## 7.2 Version Control

Version control is mendatory for any project, but especially when wanting to create a pipeline that can be used in a production environment. without it, you would 100% run into problems.

Here I pasted some snippets of the version controlling I used in this project.

### 7.2.1 Training model version

When training the model, the name is set using github.sha and github.run_id, this ensures that each model has a unique name, and that the model can be traced back to the commit and run that created it.

```
  - name: Execute Azure ML Script
uses: azure/CLI@v1
id: azure-ml-pipeline
if: ${{ inputs.train_model }}
with:
azcliversion: 2.53.0
inlineScript: |
az extension add --name ml -y
az configure --defaults group=$GROUP workspace=$WORKSPACE location=$LOCATION
az ml job create --file ./pipelines/mushroom-classification.yaml --set name=mushrooms-classification-${{
↪  github.sha }}-${{ github.run_id }} --stream
```

### 7.2.2 Model Version Retrieval

Within the “download” step of the GitHub Actions workflow, model version retrieval is performed. This step ensures that the latest version of the trained AI model is obtained from the Azure Machine Learning workspace:

```
  - name: Set model version
  uses: azure/CLI@v1
  with:
    azcliversion: 2.53.0
    inlineScript: |
      az extension add --name ml -y
      az configure --defaults group=$GROUP workspace=$WORKSPACE location=$LOCATION
      VERSION=$(az ml model list --name mushroom-classification --resource-group $GROUP --workspace-name
↪  $WORKSPACE --query "[0].version" -o tsv)
      az ml model download --name mushroom-classification --download-path ./inference --version $VERSION
↪  --resource-group $GROUP --workspace-name $WORKSPACE
```

In this step, the az ml model list command retrieves the version information for the “mushroom-classification” model. This version is then used to download the corresponding model artifacts to the specified path.

### 7.2.3 Model Artifact Storage

The downloaded model artifacts are stored within the “inference” directory, making them easily accessible for deployment and inference.

```
  - name: Download API Code for Docker
  uses: actions/download-artifact@v2
  with:
    name: docker-config
    path: inference
```

The “docker-config” artifact, which includes the downloaded model, is made available for subsequent steps, such as Docker containerization and deployment.

### 7.2.4 Model Deployment Version

When deploying the model, the name is set using the :latest tag (a v1.0 type of tag would be better, but this works).

This makes it easy to always ensure you have the latest version of the model.

```
- name: Docker Build and push
id: docker_build
uses: docker/build-push-action@v2
with:
  context: ./inference
  push: true
  tags: ghcr.io/driessenslucas/mlops-mushrooms-api:latest
```

# 8. Conclusion

In conclusion, this MLOps project effectively demonstrated the principles of developing, training, deploying, and testing a machine learning model for mushroom classification. Leveraging Azure ML, FastAPI, and GitHub Actions, the project showcased an end-to-end pipeline that can be easily adapted to real-world scenarios.

I had a lot of fun learning while doing this project, I hope my documentation is adequate at explaining what I did and why I did it :)

# 9. Useful links

- How to get github token: https://docs.github.com/en/authentication/keeping-your-account-and-data-secure/managing-your-personal-access-tokens
- How to use github secrets https://docs.github.com/en/actions/security-guides/using-secrets-in-github-actions
- How to create azure service principle to access azure services: https://learn.microsoft.com/en-us/cli/azure/azure-cli-sp-tutorial-1?tabs=bash
- Kubectl cheat sheet (for debugging): https://www.bluematador.com/learn/kubectl-cheatsheet
- create a Kubernetes cluster in azure azk: https://learn.microsoft.com/en-us/azure/aks/learn/quick-kubernetes-deploy-cli
- How to setup a github actions runner:https://docs.github.com/en/actions/hosting-your-own-runners/managing-self-hosted-runners/adding-self-hosted-runners

# Demos

(Use sound for the web app demo to hear the description being read out loud)

https://github.com/driessenslucas/MLOps-pipelines-2023-main/assets/91117911/654ceb40-4fa5-4354-b318-4921450ee955

https://github.com/driessenslucas/MLOps-pipelines-2023-main/assets/91117911/c75f7b37-0d1c-4acc-b045-bb258e13633c

https://github.com/driessenslucas/MLOps-pipelines-2023-main/assets/91117911/cd7ff6f4-3cc3-468a-aed1-70c9643b79da

## Download model (optional)

(if your model file exceeds 100 MB, You should be using the AzCopy tool for this instead.)

```
az ml model download --name ${name} --version ${version} --download-path ${path} --resource-group ${group}
  ↪  --workspace-name ${workspace}
```