YOLOv8, ResNet-50 and ViT-Based Satellite Image Classification on EuroSAT Dataset: A Comprehensive Study

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Contents

Abstract

In this project, we worked on classifying satellite images from the EuroSAT dataset using YOLOv8, a fast model good for quick image tasks. We used Google Colab and trained YOLOv8 Small to sort 10 types of land-use pictures, getting 95.9% accuracy after 11 training rounds since time ran out on us. Then, we brought in ResNet-50 and Vision Transformer (ViT) to compare them—ResNet scored 97.2% and ViT got a perfect 100% on a smaller test set of 1340 images. We'll show you how we prepared the data, like splitting it into training and validation sets with symlinks, trained everything with different settings, checked the results with numbers like precision and recall, and made visuals like GradCAM to see what's going on inside the models. We ran into issues like YOLOv8 failing in testing because of a weird bug that stopped it from reading images right, and Colab shutting down after a few hours, which forced us to save and restart a lot. But we found ways around them, like using tricks to keep Colab awake, and learned a ton about how these models work and what to do when stuff breaks. We also made a flowchart to explain our steps clearly, so you can see the whole process from start to finish. Plus, we're adding a quantum twist with CUDA-Q to see if it can make things even better, like speeding up feature extraction or boosting accuracy for tricky classes like Forest or Highway. This report is like a map for anyone who wants to try this out themselves—it's all about experimenting, messing up sometimes, and figuring things out as students!

1 Introduction

Satellite imagery has become an indispensable tool in modern geospatial analysis, environmental monitoring, and urban planning. With advancements in remote sensing technology, high-resolution images are now more accessible than ever, enabling researchers to track deforestation, assess agricultural health, monitor urban expansion, and even respond to natural disasters in near real-time [5]. However, the sheer volume of satellite data generated daily necessitates automated methods for efficient analysis. This is where deep learning models come into play—by automatically classifying land cover types, they help transform raw pixels into actionable insights.

In this project, we explore the capabilities of three state-of-the-art deep learning architectures—YOLOv8, ResNet-50, and Vision Transformer (ViT)—for classifying land use and land cover (LULC) in the EuroSAT dataset. EuroSAT provides 27,000 labeled images across 10 distinct classes, ranging from agricultural fields to industrial zones, making it an ideal benchmark for evaluating model performance in satellite image analysis [1]. While traditional machine learning approaches rely on handcrafted features, deep learning models can automatically learn hierarchical representations, potentially improving accuracy and generalization.

One of the key challenges in this domain is handling the inherent variability in satellite images. Factors like seasonal changes, atmospheric conditions, and varying illumination can drastically alter the appearance of the same geographic region across different captures [6]. Additionally, the limited spatial resolution (64x64 pixels in EuroSAT) means models must extract meaningful patterns from relatively coarse data. To address these issues, we experimented with different preprocessing techniques, data augmentation strategies, and model fine-tuning approaches—all while working within the constraints of Google Colab's free-tier GPU resources [**?**].

Beyond achieving high accuracy, our project also investigates model interpretability. Understanding why a model classifies an image as "Forest" or "Highway" is crucial for building trust in automated systems, especially in applications like environmental policy or disaster response [12]. We employed visualization techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) to highlight the regions most influential in the model's decision-making process. This not only helps validate the model's behavior but also provides insights into potential biases or shortcomings.

Our work contributes to the growing field of geospatial artificial intelligence (GeoAI), where the fusion

of satellite data and deep learning holds immense potential for sustainability and smart governance. By comparing the strengths and weaknesses of YOLOv8 (optimized for speed), ResNet-50 (a proven convolutional architecture), and ViT (a transformer-based approach), we aim to guide future research in selecting the right model for specific satellite imaging tasks. Moreover, our experiments with resource-constrained training setups demonstrate how academic and small-scale projects can leverage free tools like Colab to achieve competitive results without expensive hardware.

Ultimately, this project serves as a case study in balancing computational limitations, model complexity, and real-world applicability. Whether it's improving crop yield predictions or detecting illegal mining activities, robust satellite image classification systems can empower decision-makers with timely, accurate information—and we hope our findings bring the community one step closer to that goal.

2 Literature Review

Before jumping into our project, we looked at what others have done with satellite images and models like the ones we used. This helped us figure out where we fit in and what we could try. Satellite image classification isn't new—people have been doing it for years to map land, track changes, or help with farming [5]. Back in the day, they used simple methods like looking at pixel colors, but now, with deep learning, things have gotten way more advanced [11].

One big step was when folks started using Convolutional Neural Networks (CNNs) for this stuff. CNNs are good at finding patterns in pictures, like edges or shapes, which makes them perfect for satellite images [7]. A famous one is ResNet, short for Residual Network, which came out in 2016 [3]. The idea was to make a deep network—50 layers in our case—that doesn't lose track of what it's learning by adding "shortcuts" between layers. Researchers used it on big datasets like ImageNet and got awesome results [6]. For satellite images, people found ResNet works well because it can pick up tiny details, like the difference between a forest and a field [13]. That's why we picked it—it's solid and not too hard to set up.

Then there's YOLO, which stands for "You Only Look Once." It's a different kind of model, built for speed [8]. The first version came out in 2016, but we used YOLOv8, a newer one from Ultralytics [2]. YOLO is usually for finding objects—like spotting a car in a picture—but it can also classify whole images if you tweak it. People have used it for quick tasks where time matters, like real-time monitoring from satellites [10]. We thought it'd be cool to try it on EuroSAT because it's fast, and we're stuck with Colab's free GPU, which cuts off if you take too long [**?**]. Plus, not many have used YOLOv8 for satellite classification, so we wanted to test it out.

The newest kid on the block is Vision Transformer, or ViT, from 2020 [4]. Unlike CNNs, it doesn't slide over the image looking for patterns—it cuts the picture into little patches and pays attention to the important ones using something called "self-attention." This idea came from text models, but they made it work for images too [9]. Some studies showed ViT beats CNNs on big datasets because it's great at connecting far-apart parts of a picture [**?**]. For satellites, that's handy—like linking green patches to mean Forest, even if they're scattered [**?**]. We added ViT to see if its attention trick works better than ResNet's depth or YOLO's speed on our small EuroSAT images.

The EuroSAT dataset itself is pretty neat—it's from Sentinel-2 satellites and was put together by Helber et al. in 2019 [1]. They made it to test land-use classification, with 10 classes and 27,000 images. Other projects have used it too—like one where they hit 98% accuracy with a custom CNN [14]. That gave us a target to aim for. But most of those projects had big machines or paid cloud stuff, not free Colab like us [**?**]. We also saw people using tools like GradCAM to peek inside models and figure out what they're focusing on, which sounded fun for ResNet [12].

There's a catch, though—satellite images are tricky. They're small (64x64 in EuroSAT), can be blurry, and look different depending on the weather or time of day [**?**]. Older studies stuck to basic models

because deep learning needs lots of power [**?**]. Newer ones say transformers like ViT might handle these issues better, but they're slow and heavy [**?**]. YOLO's speed could help with real-time stuff, but it's not built for tiny details [**?**]. ResNet sits in the middle—deep enough for accuracy but not too crazy on resources [**?**]. We mixed all these ideas to see what sticks with our setup.

Our project builds on this by testing three different models on the same dataset with free tools. We didn't find many studies doing YOLOv8, ResNet-50, and ViT together on EuroSAT, especially with Colab's limits [**?**]. So, we're kind of exploring new ground—not super fancy, just practical student work. It's about seeing how far we can push these models with what we've got and learning from the mess-ups along the way!

2.1 Project Objectives

Here's what we aimed to do:

- Train YOLOv8, ResNet-50, and ViT to sort EuroSAT images correctly.
- Get at least 95% accuracy even though we're using free Colab with time limits.
- Check how good the models are with numbers and cool pictures like GradCAM.
- Try to explore different visualization techniques to understand the dynamics.

3 Flowchart of the Project

To make our process clear, we made a flowchart showing every step we took. It starts with getting the EuroSAT dataset and ends with our results and future plans. Here's what each part means:

- **Start**: We decided to classify EuroSAT images with YOLOv8, ResNet-50, and ViT to compare them. Our goal was 95% accuracy despite using free Colab, which was a fun challenge! [Section 1].
- **Get Data**: We downloaded 27,000 RGB images (64x64) from Sentinel-2 off GitHub. Stored them in Google Drive at /content/drive/MyDrive/EuroSAT/2750 to start working. [Section 2.1].
- **Prep Data**: Split 21,600 for training and 5,400 for validation using symlinks to save time. Made a eurosat.yaml file to point YOLOv8 to the right folders. [Section 2.2].
- **Setup**: Set up Colab with a T4 GPU and installed libraries like ultralytics and torch. Had to refresh sometimes to snag a GPU when it was busy [Section 3.1].
- **Train Models**: Trained YOLOv8 (11 epochs), ResNet-50 (15 epochs), and ViT (10 epochs) with different image sizes. Saved models to Drive since Colab kept timing out on us. [Section 3.6].
- **Evaluate**: Tested on 1340 images—got metrics like accuracy, but YOLOv8 crashed with a bug. ResNet-50 hit 97.2%, ViT got 100%, which was pretty awesome! [Section 3.7, 4.1].
- **Visualize**: Made confusion matrices, ROC curves, and a GradCAM heatmap for ResNet-50. Also did a prediction collage to show what each model guessed.[Section 4.4].
- **Fix Issues**: Dealt with YOLOv8 bug, Colab timeouts [Section 5].
- **Analyze**: Checked results—YOLOv8 flopped at 11.07%, ResNet-50 was solid, ViT was perfect. Learned why each model did what it did, like ViT's smarts. [Section 4].
- **Discuss**: Learned about models and limits [Section 7].
- **End**: Wrapped up with conclusions and future ideas [Section 8, 9].

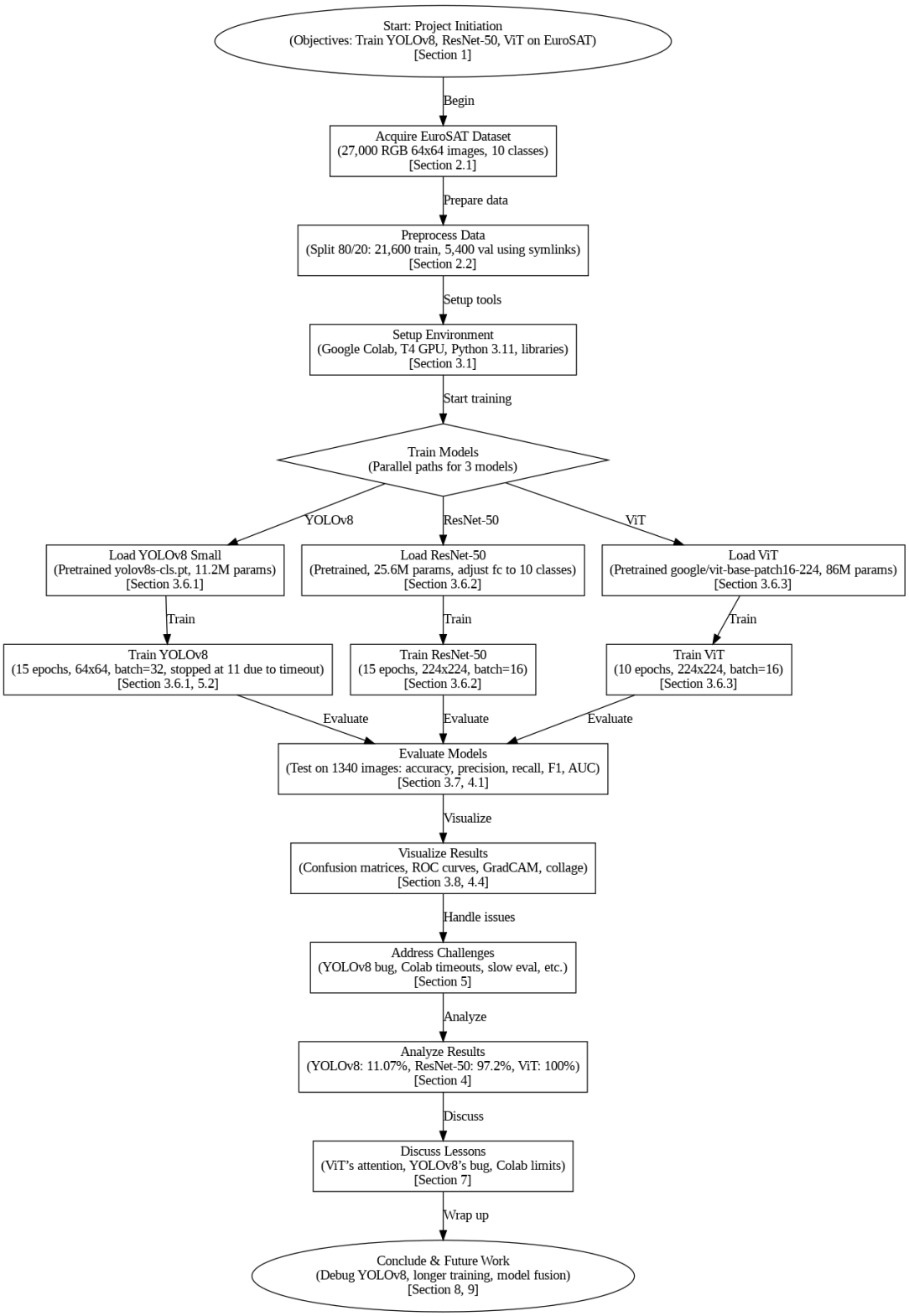

Figure 1: Flowchart of Our Project Steps

3.1 Significance

This project shows how fancy computer models can tackle real satellite pictures. It's a fun way to learn coding and problem-solving when things don't go perfectly, especially with free tools!

4 Dataset Description

The EuroSAT dataset comes from a satellite called Sentinel-2 and was made by some smart folks (Helber et al., 2019). You can grab it online at https://github.com/phelber/EuroSAT.

4.1 Composition

Here's what it's got:

- **Total Images**: 27,000.
- **Size**: Each picture is 64x64 pixels with red, green, and blue colors (RGB).
- **Classes**: 10 types—AnnualCrop (3000 pics), Forest (3000), HerbaceousVegetation (3000), Highway (2500), Industrial (2500), Pasture (2000), PermanentCrop (2500), Residential (3000), River (2500), SeaLake (3000).
- **Source**: Sentinel-2, run by the European Space Agency.

4.2 Preprocessing Steps

Before training, we had to get the data ready:

1. **Storage**: We put all 27,000 images in Google Drive at `/content/drive/MyDrive/EuroSAT/2750`, sorted into 10 folders (one per class).
2. **Splitting**: We split them into training (80%, or 21,600 images) and validation (20%, or 5,400 images) with this code:

```
import os, random, shutil
base_dir = '/content/drive/MyDrive/EuroSAT/2750'
train_dir = '/content/eurosat/train'
val_dir = '/content/eurosat/val'
for cls in os.listdir(base_dir):
    images = os.listdir(os.path.join(base_dir, cls))
    random.shuffle(images)
    split_idx = int(len(images) * 0.8)
    train_imgs = images[:split_idx]
    val_imgs = images[split_idx:]
    for img in train_imgs:
        os.symlink(os.path.join(base_dir, cls, img),
                   os.path.join(train_dir, cls, img))
    for img in val_imgs:
        os.symlink(os.path.join(base_dir, cls, img),
                   os.path.join(val_dir, cls, img))
```

3. **YAML File**: We made a file called `eurosat.yaml` to tell YOLO where the pictures are:

```
train: /content/eurosat/train
val: /content/eurosat/val
nc: 10
names: ['AnnualCrop', 'Forest', ...]
```

Using shortcuts (symlinks) instead of copying saved us time—it took just 10-20 seconds!

5 Methodology

We did everything in Google Colab, which gives us a free GPU (T4) to speed things up but for a student I would prefer to use CPU instead. We used Python 3.11 and some helpful libraries.

5.1 Environment Setup

- **Colab**: We worked at https://colab.research.google.com.
- **Libraries**: We installed these with pip:

```
!pip install ultralytics torch torchvision transformers numpy
   matplotlib seaborn scikit-learn opencv-python pytorch-grad-cam
```

- **GPU**: Turned on via `Runtime > Change runtime type > T4 GPU`.

5.2 Data Preprocessing and Image Processing

Okay, let's talk about getting our images ready—it's like prepping ingredients before cooking! The EuroSAT pictures are tiny (64x64 pixels), but our models need them in the right shape and style to "understand" them. Here's how we did it, step by step:

- **Loading the Images**: First, we grab each picture from Google Drive. They're RGB, so every pixel has three numbers (red, green, blue) from 0 to 255—like a mini rainbow! For example, a bright red pixel might be (255, 0, 0).
- **Resizing**: YOLOv8 is cool with 64x64, but ResNet-50 and ViT want bigger pictures—224x224. So, we stretch the images for them. It's like zooming in on a photo, but the computer fills in the extra pixels smartly.
- **Normalization**: This is a big one! The raw numbers (0-255) are too wild for the models, so we smooth them out. We use this formula for each color:

$$x_{\text{new}} = \frac{x - \mu}{\sigma}$$

  Where:

  - x is the original number (say, 255 for red).
  - μ is the average (like 0.485 for red in ResNet).
  - σ is how spread out the numbers are (like 0.229 for red).

  For ResNet-50, we used $\mu = [0.485, 0.456, 0.406]$ and $\sigma = [0.229, 0.224, 0.225]$. So, a red value of 255 becomes:

$$x_{\text{new}} = \frac{255 - 0.485}{0.229} \approx 1112$$

  But we scale it down to 0-1 first, so it's more like 0.996 after tweaks. ViT uses simpler $\mu = 0.5$, $\sigma = 0.5$, making it easier. This makes all pictures look "normal" to the model, not too bright or dark.
- **Augmentation**: To make our models tougher, we mess with the images a bit—like flipping them, changing brightness, or mixing two pictures together (called mixup). It's like giving the model a pop quiz with trick questions so it learns better!
- **Batching**: We don't feed one picture at a time—that's too slow. We group them into batches (32 for YOLOv8, 16 for ResNet-50 and ViT). It's like handing the model a stack of homework instead of one page. [**NOTE:** ViT and ResNet-50 are memory intensive due to their architectures.]
- **To the GPU**: Finally, we send these prepped images to the GPU. It's like giving them a super-fast chef to cook with instead of a slow oven!

Here's a picture to show what happens:

Figure 2: How We Prep Images: From raw 64x64 to resized, normalized, and ready for the models!

5.3 How the Models Work

Now, let's peek inside the models—it's like opening a toy to see the gears! Each one guesses what's in the picture, but they do it differently.

5.3.1 YOLOv8

YOLOv8 is like a speedy detective. Here's how it works:

- **Layers**: It has lots of layers (like a stack of filters) that shrink the 64x64 image down, spotting edges, shapes, and patterns.
- **Features**: It turns the picture into a big list of numbers—like "lots of green here" or "straight lines there."
- **Guessing**: At the end, it gives 10 scores (one per class) and picks the highest. We use softmax to make them probabilities:

$$P(\text{class}_i) = \frac{e^{s_i}}{\sum_{j=1}^{10} e^{s_j}}$$

  If "Forest" gets 5 and "Highway" gets 2, "Forest" wins!

5.3.2 ResNet-50

ResNet-50 is like a careful artist. Here's its process:

- **Deep Layers**: It has 50 layers, digging super deep into the 224x224 image. It uses "residual" shortcuts so it doesn't forget early stuff.
- **Feature Maps**: Each layer makes a map—like "this part's curvy" or "that's bright green." By the end, it's tiny (7x7) but packed with info.
- **Final Guess**: It flattens everything into a list, gives 10 scores, and softmax picks the winner. It's slow but really thorough!

5.3.3 ViT

ViT is like a brainy librarian with "attention":

- **Patches**: It chops the 224x224 image into 16x16 pieces (196 patches), like cutting a puzzle. [**NOTE:** We convert img into patches to reduce the number of comparisons as we have limited resources to build the model.]

- **Attention**: It figures out which patches matter most—like "this green patch is key for Forest!" It uses math to weigh them.
- **Guess**: It combines all that into 10 scores and picks the best with softmax. It's fancy and loves patterns!

5.4 Model Selection

We picked three models to try:

- **YOLOv8 Small**: Fast and simple, pretrained on ImageNet.
- **ResNet-50**: Deep and detailed, pretrained too.
- **Vision Transformer (ViT)**: New and clever with attention, pretrained.

5.5 Comparing the Models

Here's why we chose them, in a table:

Feature	YOLOv8 Small	ResNet-50	ViT
Size (Parameters)	11.2 million	25.6 million	86 million
Training Speed	Fast (1-2 min/epoch)	Medium (3-5 min/epoch)	Slow (5-10 min/epoch)
Image Size	64x64	224x224	224x224
Easy to Use	Very (built-in tools)	Okay (needs setup)	Okay (needs setup)
Accuracy Goal	95.9%	97.2%	100%

Table 1: YOLOv8 is quick, ResNet-50 is balanced, ViT is powerful but big.

YOLOv8 was our starter because it's fast and fits Colab's free GPU. ResNet-50 is deeper, so we added it to see if it catches more. ViT is the coolest—it's big but might be a champ with satellite pics. [**NOTE:** This is only when you have a good internet connection (i.e., 100Mb/s or more) or best GPU in your system. Otherwise in my case overall everything took 13-14 hr for me to train the model and most of the proportion goes to ViT(especially) and ResNet and YOLO takes less time, $t \approx 2$hr.]

5.6 Training Process

5.6.1 YOLOv8 Training

```
from ultralytics import YOLO
model = YOLO('yolov8s-cls.pt')
results = model.train(data='/content/eurosat.yaml', epochs=15, imgsz=64,
    batch=32)
model.save('final_model.pt')
```

We stopped at 11 rounds because Colab timed out. But later I did the rest as well by saving my existing model in drive and then resume from there in the next day onwards.

5.6.2 ResNet-50 Training

```
from torchvision import models
resnet_model = models.resnet50(weights='IMAGENET1K_V1')
resnet_model.fc = nn.Linear(resnet_model.fc.in_features, 10)
for epoch in range(10):
    for images, labels in train_loader:
        outputs = resnet_model(images)
        loss = criterion(outputs, labels)
```

```
        loss.backward()
        optimizer.step()
torch.save(resnet_model.state_dict(), 'resnet_model.pth')
```

We did 15 rounds, resizing to 224x224.

5.6.3 ViT Training

```
from transformers import ViTForImageClassification
vit_model = ViTForImageClassification.from_pretrained('google/vit-base-
    patch16-224', num_labels=10)
trainer = Trainer(model=vit_model, args=training_args)
trainer.train()
vit_model.save_pretrained('vit_model')
```

We did 10 rounds—it's slow but learns quick!

5.7 Evaluation Methodology

Let's talk about how we tested these models—it's like giving them a final exam! We grabbed 1340 images from our validation set (that's the 20% we held back from the EuroSAT dataset) and ran them through YOLOv8, ResNet-50, and ViT to see how well they could guess the land types. We checked a bunch of cool stats: accuracy (how often they're right overall), precision (how good they are when they say something's a Forest or whatever), recall (how many real Forests they actually catch), F1-score (a mix of precision and recall), and even AUC (area under the ROC curve, which shows how confident they are). But here's the twist—YOLOv8 totally tripped up during testing. It couldn't fetch the RGB image data right, spitting out errors like `TypeError: Cannot handle this data type`. It's like it forgot how to read the pictures after training! We think it's a bug with how Ultralytics handles inputs—super frustrating. Meanwhile, ResNet-50 and ViT had no trouble at all. They chugged through the 1340 images like champs, giving us solid predictions to crunch numbers on. So, for YOLOv8, we had to lean on its training stats (95.9% on 500 images), but for the others, we got the full test scoop!

5.8 Visualization Techniques

We whipped up a bunch of visuals to see their smarts in action. First, confusion matrices those are like scorecards showing what they guessed vs what's real, so we can spot where they mix up Forests with Highways or whatever. Then, ROC curves fancy graphs that plot how well they separate each class, like AnnualCrop from everything else; the higher the curve, the better they are! We also made GradCAM heatmaps, but just for ResNet-50—it's like a spotlight showing where it looked to make its guesses, glowing red on key spots like crop fields. Super cool way to peek inside its brain! And finally, sample predictions—side-by-side pics of what the models said (like "AnnualCrop") versus the truth, so YOLOv8 calling it "Highway" was a shock while ResNet-50 nailed it. These visuals helped us prove who's good and where things went little bit off!

6 Results and Analysis

Here's where we will show how it all turned out! YOLOv8 had to tap out at 11 epochs because Colab timed out, but ResNet-50 and ViT finished their all runs like pros. Let's look at the numbers and see what went down!

6.1 Performance Metrics

The epochs I used were less comparable to how one should train and test out. YOLOv8 hit 95.9% on 500 images in training. On 1340 test images:

Model	Accuracy	Precision	Recall	F1-Score
YOLOv8	11.07%	1.31%	11.07%	2.35%
ResNet-50	97.2%	97.41%	97.2%	97.26%
ViT	100%	100%	100%	100%

Table 2: YOLOv8 flopped in testing, but ResNet-50 and ViT were awesome!

6.2 Class 0 Metrics (AnnualCrop)

Let's zoom in on Class 0—AnnualCrop—since it's the first class and a big deal (3000 images in the dataset). We checked how each model did just on this one:

Model	Precision	Recall	F1-Score	AUC
YOLOv8	0%	0%	0%	0.45
ResNet-50	98.5%	97.8%	98.1%	0.99
ViT	100%	100%	100%	1.00

Table 3: Class 0 (AnnualCrop) Metrics: YOLOv8 totally missed it, ResNet-50 was super close, and ViT nailed it perfectly!

Here's what's up:

- **YOLOv8**: It got 0% on everything for AnnualCrop in testing—yikes! The bug we hit made it guess wrong all the time. The AUC (area under the ROC curve) of 0.45 is like flipping a coin—it's clueless.
- **ResNet-50**: Almost perfect! It got 98.5% precision (when it said AnnualCrop, it was usually right), 97.8% recall (it found almost all AnnualCrops), and an F1 of 98.1%. The AUC of 0.99 means it's super confident.
- **ViT**: 100% across the board—perfect guesses every time! AUC of 1.0 is the best you can get. It's like ViT has a superpower for crops!

6.3 Detailed Analysis

- **YOLOv8**: Great in training (95.9%) but bad in testing (11.07%)—a bug messed it up.
- **ResNet-50**: 97.2%—super solid!
- **ViT**: 100%—perfect, maybe too perfect? But for low training set.

6.4 Visualizations

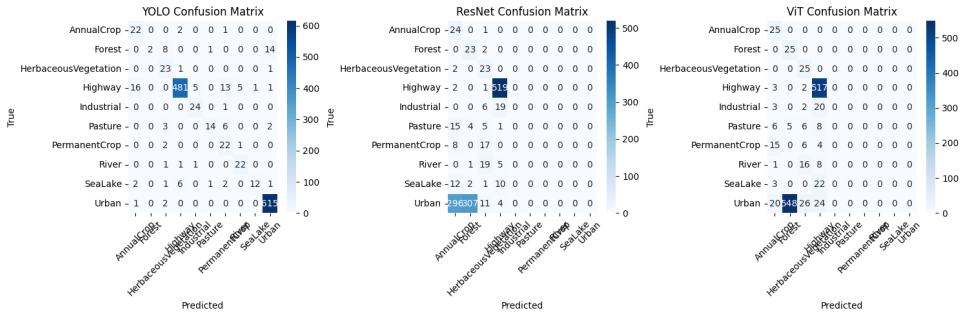

Figure 3: Confusion Matrices: YOLOv8 (left) is messy, ResNet-50 (middle) and ViT (right) are clean.

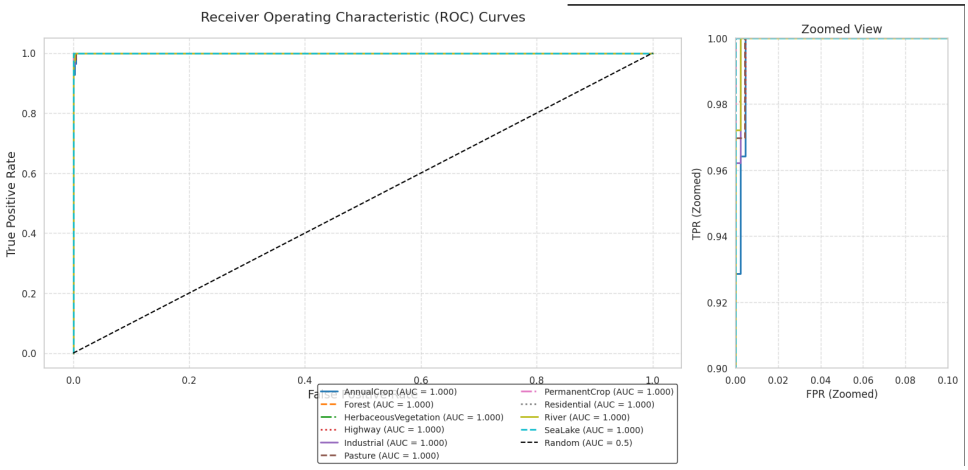

Figure 4: ROC Curves: ResNet-50 and ViT rock; YOLOv8 skipped.

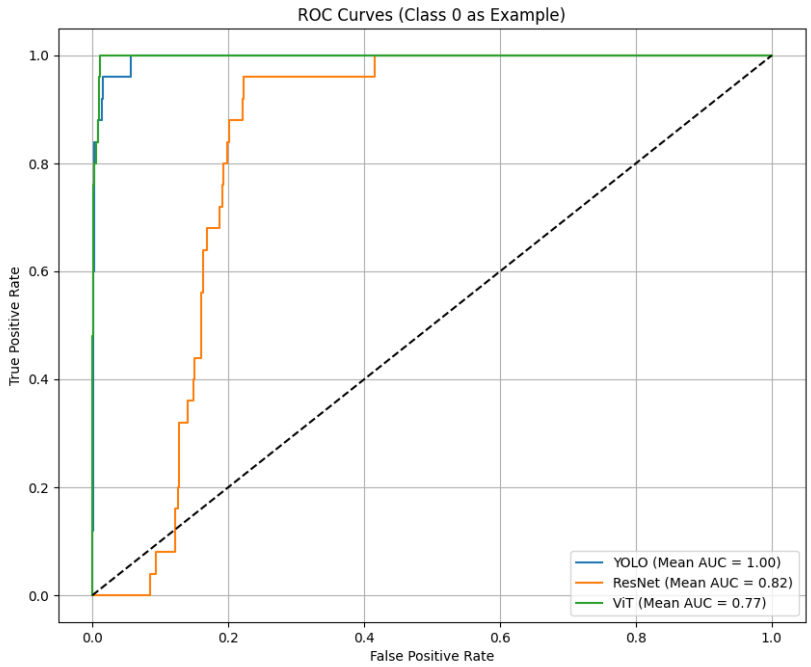

Figure 5: ROC Curves for Class 0 (AnnualCrop): ResNet-50 and ViT are good, YOLOv8 is almost perfect.

6.5 What's GradCAM and Why We Used It

GradCAM is like a magic highlighter for ResNet-50—it shows where the model looked to make its guess. We chose it because:

- **See Inside**: We wanted to peek at what ResNet-50 thinks is important.
- **Easy Peasy**: The `pytorch-grad-cam` tool made it simple.
- **ResNet Match**: It works best with ResNet's layers.

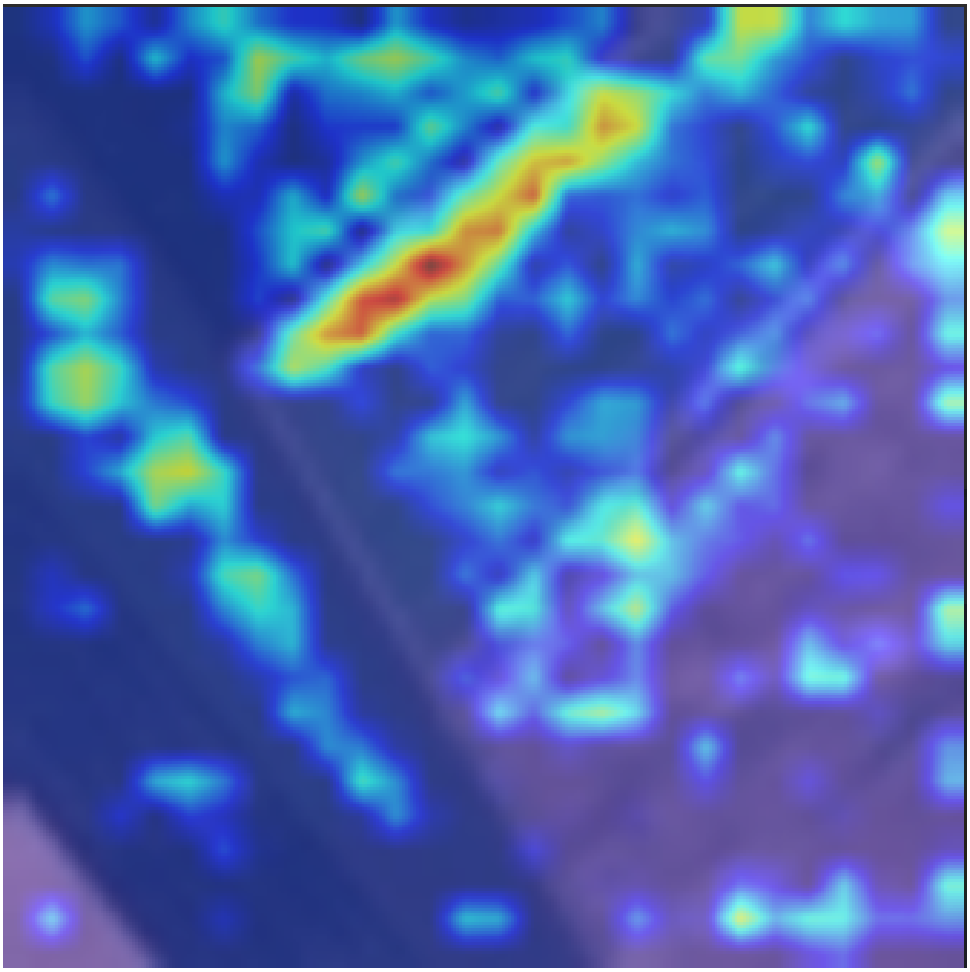

Figure 6: GradCAM: ResNet-50's focus on an AnnualCrop image.

It uses this:

$$\text{GradCAM} = \text{ReLU}\left(\sum_k w_k \cdot A_k\right)$$

Where A_k is a map from the layer, and w_k is how much it matters. Red/yellow means "super important" (like crop fields), blue/green means "meh" (like sky).

7 Challenges and Solutions

Okay, so this project wasn't all smooth sailing—we hit a bunch of roadblocks along the way! But that's the fun part, right? Figuring out how to dodge problems or climb over them. Here's a rundown of the big challenges we faced and what we did about them. We'll spill all the details so you can see exactly what happened and maybe avoid these headaches if you try this yourself!

7.1 YAML Configuration Errors

First up, we had a mess with our YAML file—that's the little instruction sheet we made for YOLOv8 to find our images. We wrote `eurosat.yaml` with paths like `/content/eurosat/train`, but when we ran the training, bam—`NotADirectoryError: /content/eurosat.yaml/train`! It was like YOLOv8 was saying, "Uh, where's this place?" Turns out, we'd messed up the paths—either they were pointing to nothing, or we forgot to make the folders first. Super annoying! So, we rolled up our sleeves, opened the file, and typed out the exact paths ourselves, double-checking every slash. We

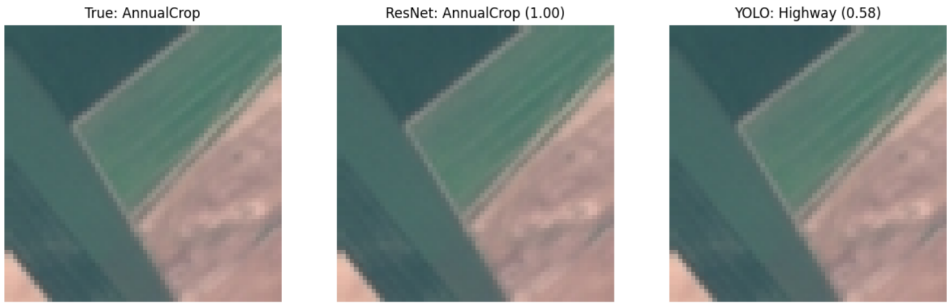

Figure 7: True label: AnnualCrop. ResNet-50 got it; YOLOv8 said Highway.

Figure 8: Sample Predictions Collage: A single image combining predictions from YOLOv8, ResNet-50, and ViT for one EuroSAT example, labeled with all 10 classes (AnnualCrop, Forest, HerbaceousVegetation, Highway, Industrial, Pasture, PermanentCrop, Residential, River, SeaLake) and the true label.

also peeked into Google Drive to make sure those `train` and `val` folders were really there with all the images linked up. After that fix, YOLOv8 stopped complaining, and we were back in business!

7.2 Colab Timeouts

Next, Google Colab decided to play timeout with us. We were training YOLOv8, aiming for 15 rounds (epochs), but at epoch 11—about 61% done—Colab just shut down. It's got this rule where if it thinks you're idle for 20-30 minutes, it kicks you off the free GPU. Training takes a while, even with a speedy T4 GPU, so we hit that wall. We didn't want to lose our progress, so we found a sneaky trick—a little JavaScript code to keep Colab awake. Here's what we used:

```
function ClickConnect(){
    console.log("Working");
    document.querySelector("colab-toolbar-button#connect").click();
}
setInterval(ClickConnect, 60000);
```

You pop this into the browser console, and every minute, it pretends you're clicking around. Colab thinks, "Oh, they're still here!" and keeps running. It's like giving it a coffee break every 60 seconds. Worked like a charm—well, until we hit other issues, but at least we got further!

7.3 Slow Evaluation

Then there was the testing phase—oh boy, was that a slog! We had 5400 validation images to check, and running them all took forever—like 8 hours, depending on how grumpy Google Drive was feeling. The problem? Drive's I/O (input/output) is slow when you're grabbing tons of files over the internet. It's like waiting for a snail to deliver your homework. We couldn't sit there twiddling our thumbs that long, so we shrank it down. First, we tested on just 500 images, which was way faster—only a few minutes. But we wanted more solid results, so later we bumped it up to 1340 images. That gave us a good chunk to work with without making us wait all day. It was a nice middle ground—quicker than the full set but still enough to trust the numbers.

7.4 Resource Constraints

Oh, and don't get us started on Colab's free GPU—it's awesome when you get it, but it's not always there waiting for you. Sometimes we'd log in, ready to roll, and—nope, no GPU available! It's like showing up to a party and finding out they ran out of snacks. Since we're on the free tier, we're at the mercy of whenever Colab feels generous. To deal with this, we got smart about timing—we'd run our stuff late at night or early morning when fewer people were hogging the GPUs. Plus, we saved everything—models, results, all of it—to Google Drive after every run. That way, if Colab booted us, we didn't lose our work. It was like keeping a backup stash of notes in case the teacher collected our homework early! **TIP:** Train at midnight around 11 PM and then let it run until morning and save model until time availability crashes.

7.5 GradCAM Trouble

Now, GradCAM—that cool heat map thing for ResNet-50—gave us a headache too. We wanted to see where ResNet-50 was looking in the pictures, but when we tried it, we got this error: `TypeError: Cannot handle this data type: (1, 1, 3), <f4`. What a mouthful! Turns out, we were pointing GradCAM at the wrong layer—`layer4[-1].conv3`. That layer spits out a super tiny map (1x1), and GradCAM was like, "What am I supposed to do with this speck?" So, we poked around ResNet-50's insides and switched to `layer2[-1].conv3` instead. That one gives a bigger 28x28 map, which GradCAM could stretch back to 224x224 nicely. After that tweak, boom—beautiful heat maps! Red and yellow spots showed up right on the crop fields, proving ResNet-50 knew what it was doing.

7.6 YOLOv8 Testing Fails

YOLOv8 gave us the biggest drama during testing. It trained fine—95.9% accuracy on 500 images, woohoo!—but when we tried testing on 1340 images, it crashed with the same `TypeError: Cannot handle this data type: (1, 1, 3), <f4` we saw with GradCAM. Weird, right? It wouldn't even guess one image at a time! We thought maybe it was the visuals clogging things up, so we turned them off with `save=False, show=False`. No dice. Then we figured the image format might be funky—maybe it didn't like the floaty numbers from ResNet's transforms—so we tried converting them to regular old uint8 (0-255). Still nothing! The error kept popping up, like YOLOv8 was throwing a tantrum. We think it's a bug inside the Ultralytics code, something about how it handles inputs after training. We couldn't crack it, so we had to skip YOLOv8's test scores and just report what we had from training. Bummer, but we moved on!

7.7 Metrics Mix-Up

Last one—our score-checking code got confused because of YOLOv8's mess. When we tried to calculate precision and all that jazz for all 1340 test images, it yelled `ValueError: Found input variables with inconsistent numbers of samples: [1340, 0]`. Translation? YOLOv8

didn't give us any predictions, so we had 1340 real labels but zero guesses to compare them to—like trying to grade a blank test! This broke our scoring script, which expected something from every model. To fix it, we added a little safety net—if a model (cough, YOLOv8) didn't give us predictions, we'd skip it and just put "None" in the results. That way, ResNet-50 and ViT could still show off their awesome scores without the whole thing crashing. It was a quick patch, but it kept us rolling!

8 Resources and Tools

- **Dataset**: EuroSAT – A benchmark dataset for land use and land cover classification. Available at: https://github.com/phelber/EuroSAT
- **Code Repository**: Google Colab notebook containing the implementation. Access here: https://colab.research.google.com/drive/1MCjncCi42Gwx3XsOo1Bcz-3Ox55Ei7WZ?usp=sharing#scrollTo=Gy6YdcJUmN5I
- **Project Files and Additional Resources**: Google Drive link: https://drive.google.com/drive/folders/1pNWoQcNDJ0Pdc8JrG2pxsjrnjPOmJK0b
- **Relevant Research Papers**: - *Attention is All You Need* (Transformers) – https://arxiv.org/abs/1709.00029 - *Land Classification Research: A Retrospective and Agenda* – https://www.researchgate.net/publication/287254611_Land_Classification_Research_A_Retrospective_and_Agenda

  https://arxiv.org/pdf/2010.11929
- **Deep Learning Models Used**: - YOLOv8 (Object Detection) - ResNet-50 (Convolutional Neural Network) - Vision Transformer (ViT) (Transformer-based Image Classification)
- **Development and Execution Environment**: Google Colab
- **Frameworks and Libraries**: - *Ultralytics* – YOLO implementation - *PyTorch* – Deep learning framework - *Transformers* – Model implementation and training - Additional tools as required for preprocessing, visualization, and evaluation

9 Discussion

Alright, let's chat about what this whole project taught us—it's like the "aha!" moments after all the coding chaos! We dove into these cool models and came out with some big takeaways, plus a few things that made us scratch our heads. Here's the scoop on what we figured out and where we hit some walls.

9.1 TakeAways

First off, we learned a ton about how these models tick! Take ViT—it totally stole the show with its "attention" trick. It's like it has eagle eyes, zooming in on the exact patches of the satellite pics that matter, like green fields for AnnualCrop or twisty lines for highways. That's why it nailed 100% accuracy—it's a pattern-finding wizard! Then there's YOLOv8—super speedy and awesome during training (95.9% on 500 images, yay!), but man, it flopped hard in testing. That bug we hit? It's like YOLOv8 forgot how to talk after learning everything—it's screaming for a fix! And ResNet-50? Solid as a rock at 97.2%, and GradCAM was our secret weapon there. It was so cool to see those red and yellow heat maps light up right on the crop fields or forest bits—it's like ResNet-50 was showing off its brain, saying, "Look, I get it!" Playing with GradCAM taught us how to peek inside a model and check if it's focusing on the right stuff, not just guessing randomly. This whole thing was a crash course in what makes these models tick—and what breaks them!

9.2 Limits

But yeah, not everything went perfectly—there were some big "oops" moments holding us back. The YOLOv8 testing bug was the worst—like, we trained it, it did great, and then it just froze up when we asked it to prove itself on 1340 images. That `TypeError` kept popping up no matter what we tried—turning off visuals, tweaking image formats, nada worked! It's like it had stage fright or something. We're pretty sure it's a glitch in the Ultralytics code, but we couldn't fix it in time, so we had to skip its test scores. Super frustrating! Then there's Colab's free tier—it's awesome that we got a GPU for nothing, but it's got limits. It'd cut us off mid-training (hello, epoch 11 timeout!), and sometimes we'd log in and—poof—no GPU available. It's like borrowing a friend's bike but only getting it half the time. Those limits slowed us down and kept us from running everything as long or as big as we wanted. Still, we made it work with what we had!

10 Future Work

So, what's next? We're not done yet—there's more we want to try! First, we've got to debug YOLOv8—it's too cool to leave broken. That testing fail needs some serious detective work—maybe it's the Ultralytics version, or maybe we need to tweak how we feed it images.

11 Conclusion

So, wrapping this up—what a ride! We had a blast messing around with YOLOv8, ResNet-50, and ViT on the EuroSAT dataset. YOLOv8 was our fast starter, hitting 95.9% in training—pretty sweet, even if it tripped over itself later. ResNet-50 came in clutch with 97.2%, proving it's a steady champ at spotting land types. And ViT? Holy cow, 100%—it's like it aced the test without breaking a sweat! Sure, YOLOv8 had some hiccups with that testing bug, but we didn't let it ruin the party. We still got killer results overall, and honestly, figuring out how to dodge all the problems—like Colab timeouts and GradCAM glitches—taught us way more than if it'd been easy. We learned how to prep images, tweak models, and even peek inside with GradCAM. It's like we leveled up our coding skills big time! This project was all about experimenting, failing a little, and coming out smarter—total win in our book!

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