# **EUROSAT LAND COVER CLASSIFICATION**

INFO6147-Deep learning with python

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## **ABSTRACT**

- The project represent a deep learning-approach to classify satellite image into various land cover types using the RGB version of the EuroSAT dataset.
- A ResNet-50 convolutional neural network, pretrained on the ImageNet was finetuned over 27,000mRGB sentinel-s Images of 10 different classes like River, Industrial, Residential, Agricultural and so on.
- The model enhanced high accuracy through data argumentation, normalization and optimized training.
- To enhance the interpretability, GRAD-CAM was integrated to visualize classspecific regions influenced on the model's prediction.
- A user-friendly web interface developed using Streamlit developed via ngrok.

# Introduction

- The main object of the project is to build a CNN-based classifier(ResNet-50) to accurately label the land covers from the satellite images.
- The dataset contains over 27000 labeled satellite images of 10 land cover types.
- ResNet-50 trained on ImageNet has been used as the CNN
- To improve the transparency, GRAD-CAM was used to generate visual heatmaps
- Visual heatmap shows which part of an image the model focused on during its prediction.
- It was wrapped in a user-friendly streamlit web application making it easy to upload an image and view the prediction along with the heatmap.

# Methodology

#### **Dataset Selection**

- Dataset source: <a href="https://zenodo.org/records/7711810#.ZAm3k-zMKEA">https://zenodo.org/records/7711810#.ZAm3k-zMKEA</a>
- Dataset contains 27,000 images of 10 classes.
- RGB version of EuroSAT has been used for this project.
- It contains R,G,B frequency bands encoded as JPEG images.

#### **Data preprocessing**

- Image resizing: Resized all images into 224\*224 pixels(resNet-50 input)
- Tensor conversion and ImageNet standard normalization for the better regularization and the performance of the model.
- Train-validation split (80%-20%)
- Loaded the data for both training and validation with batches of 32.

#### Model selection and architecture

- Model selection: ResNet-50
- Why ResNet-50

Deep 50-layer architecture

Proven performance in image classification, object detection and transfer learning

It extract rich spatial features from EuroSAT satellite images

Model architecture:

Initial layers(1\*conv2d layers)

16 bottle neck blocks each has 3 conv layers

Final layer which is replaced with output size=10

- Relu has been added to introduce non-linearity after each convolutional layers
- BatchNorm2d also added to stabilize the training.

#### **Model Training**

- Training and evaluation have been done for fine-tuned ResNet-50 model on the EuroSAT dataset.
- Model is trained using CrossEntropyLoss and optimized via SGD with learning rate of 0.001 over 5 epochs.
- Evaluated the performance using validation accuracy and training loss and validation loss.
- A separate prediction function has been added to predict the confidence score
- Softmax function was used to convert the raw scores into probability distribution across all classes.

#### **Evaluation**

To evaluate the performance of the model, accuracy has been calculated.

#### Epoch 1:

Loss: 1.8022

Training Accuracy: 50.9%

Validation Accuracy: 69.5%

#### Epoch 2:

Loss: 0.9513

Training Accuracy: 77.2%

Validation Accuracy: 84.3%

#### Epoch 3:

Loss: 0.5725

Training Accuracy: 85.2%

Validation Accuracy: 85.9%

#### • **Epoch 4**:

Loss: 0.4003

Training Accuracy: 88.9%

Validation Accuracy: 92.0%

#### • Epoch 5:

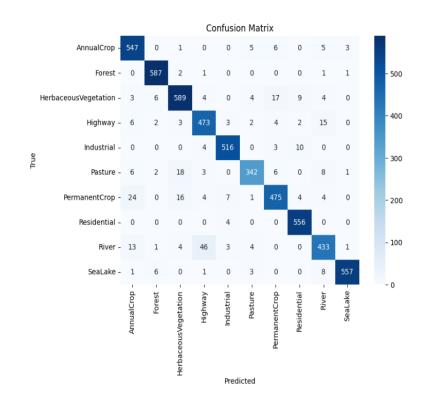
Loss: 0.3144

Training Accuracy: 90.7%

Validation Accuracy: 93.9%

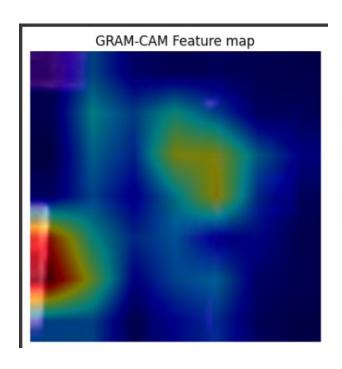
- The model shows steady improvement in both training and validation accuracy
- The accuracy reached to 93.9% from 69.5%.

#### **Confusion matrix**



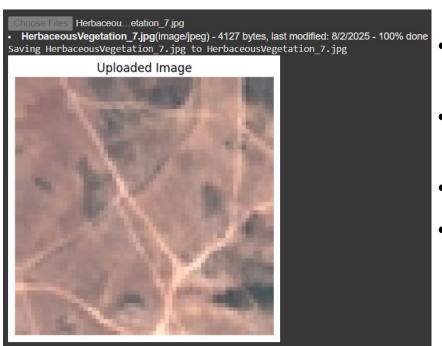
- Confusion matrix indicates that the ResNet model exceptionally well in classifying land cover from EuroSAT dataset.
- Categories like forest, herbaceous vegetation, Sea lake and residential are classified with high accuracy
- However, model struggles to classify categories Such as river, pasture due to visual similarity.

# **GRAD-CAM Feature map**



- The figure shows the GRAD-CAM(gradient Gradient-weighted class
  - activation mapping) feature map of class0(annual crop).
- It highlights the important regions in the image that the ResNet focused on while making predictions.
- The Red/yellow areas represent the regions with high influence on
  - prediction
- Blue areas indicate the low contribution to the classification

## Results



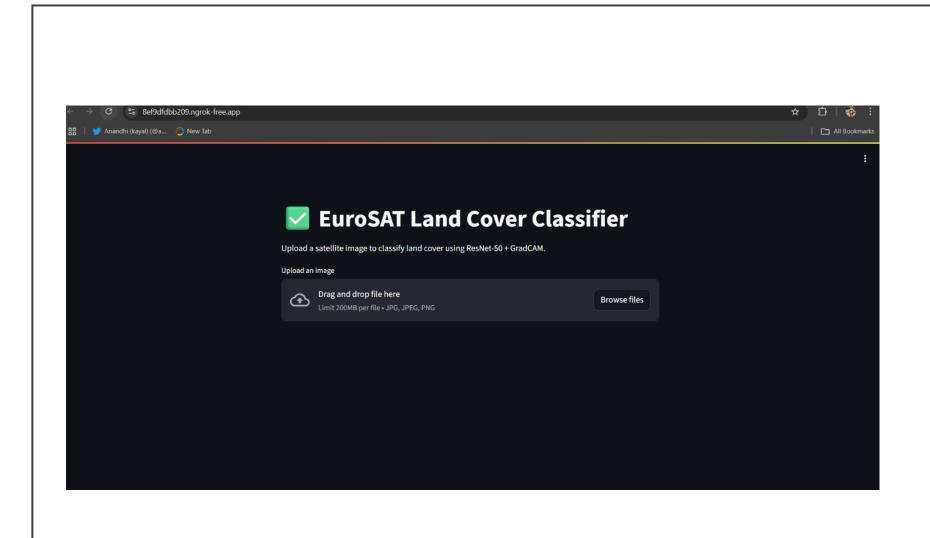
- To enable the real-time predictions, an image upload feature was implemented.
- Using the upload menu, user can upload the satellite image directly.
- Results the immediate visual feedback to the user.
- Also Predicted label and its corresponding confidence score have been printed using predict\_resnet()

# **Integration with GPT-40**

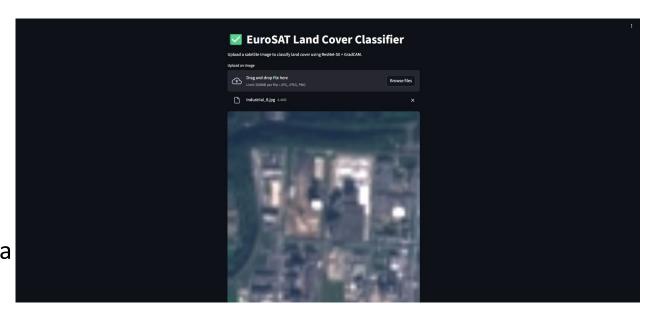
- To enhance the interpretability along with the resNet-50 prediction, GPT-40's multi-model capabilities were integrated into this project.
- A custom function converts the uploaded satellite image into a base64 format and send to GPT-40 via API along with the prompt asking the model to classify the image.
- Returns a response with its prediction.

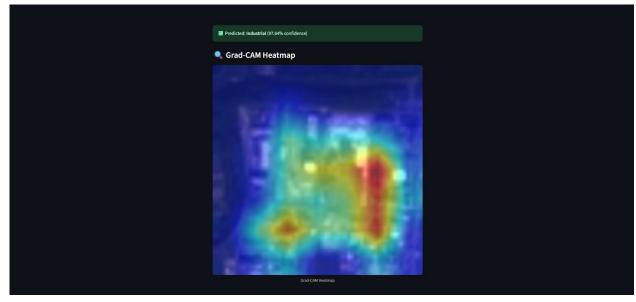
# Streamlit web application integration

- To make the classification model accessible and interactive, a web application was developed using streamlit.
- The entire setup is wrapped inside a streamlit interface with user friendly prompt.
- When the user upload an image, it results the sample images that has been uploaded, predict the output along with the confidence score and heatmap.



These figures show the uploaded image via upload option and showing its prediction. and the heatmap of the image





# **Conclusion**

- The project successfully demonstrated the power of deep learning, specifically ResNet-50 in automating land cover classification using satellite imagery.
- ResNet-50 model achieved high classification accuracy with validation accuracy of 93% by the final epoch.
- The model effectively distinguished between 10 different land cover types.
- To enhance the interpretability, GRAD-CAM was integrated to visualize the heatmap of the images.
- The heatmaps help users to understand which part of the image influenced the model's prediction.
- Integrated with GPT-40 can understand the different response from the models.
- The entire system was deployed in a streamlit web UI, allowing users to upload their own satellite images, receive the predictions and view the GRAD-CAM images from a browser.
- In summary, the project illustrates a full pipeline from training to deployment, highlighting how a
  deep learning can classify the images from the satellite.

# Questions?

# thank you