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SATELLITE IMAGE TIME SERIES ANALYSIS FOR CROP MAPPING USING U-Net, SENTINEL DATASET

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Abstract : This research project uses the U model to study time series data, from the 'Sentinel 2 – Munich' dataset with the goal of improving crop mapping accuracy. By tackling data imbalances our research enhances the precision of crop mapping, which's crucial for agricultural practices. Through data preprocessing and feature extraction techniques the U Net model shows an increase in accuracy by 90.0882%. This analysis offers insights into how crop are distributed over time and space leading to more dependable mapping results. Suggestions emphasize the need to address data imbalances for crop mapping applications providing approaches for precise and efficient crop monitoring. Ultimately this study has implications, for enhancing food security and optimizing resource allocation in agriculture**.**

IndexTerms : U-Net, Convolutional Kernels, Normalization.

INTRODUCTION

The exploration of crop mapping and monitoring has become crucial in the realm of agriculture and land management due, to its potential to enhance food security optimize resource distribution and improve farming techniques. An essential aspect of this effort involves using satellite images datasets like Sentinel 2, which provide researchers with information about the spatial and temporal distribution of crops. In this context the dataset highlighted in the study "Sentinel 2 Time Series Analysis with 3D Feature Pyramid Network and Time Domain Class Activation Intervals for Crop Mapping" plays a role in pushing forward crop mapping research.

This specific dataset, extracted from the dataset presented in the research paper "Multi Temporal Land Cover Classification with Sequential Recurrent Encoders " is a resource for the scientific community. Its release allows for comparisons, with research findings and facilitates the verification and replication of results. The dataset consists of time series data captured by the Sentinel 2 satellite across 30 acquisitions within a year. This extensive temporal data provides researchers with a view of changing landscapes aiding in pinpointing where and when different crops are grown.

One notable aspect of this dataset is its ground truth information, which includes segmentation images showcasing crops within each sample.
This segmentation goes beyond boundaries. Covers a whole year assigning each pixel a class label based on the crops grown in 2016 and 2017. As a result this dataset provides insights, into crop distribution and rotation patterns over years.

However it's important to recognize that this dataset comes with its set of challenges primarily due to data imbalances. Addressing these imbalances and extracting insights from the dataset present a research puzzle. Researchers working with this dataset must tackle issues related to data preprocessing feature extraction and classification to improve the accuracy of crop mapping efforts.

Our main goal in this study is to analyze and make use of this dataset focusing on advancing our understanding of crop mapping using Sentinel 2 time series data. We aim to explore methods and techniques for deriving insights from the dataset contributing to advancements in the field overall. Additionally our research aims to address data imbalance by proposing solutions to enhance the usefulness and reliability of the dataset, in crop mapping applications.

In essence the dataset highlighted in our research paper offers an opportunity for researchers to delve into the nuances of crop mapping using Sentinel 2 satellite imagery.

By utilizing this asset our goal is to impact the progress of crop mapping methods, which can have broad effects, on the sustainability and effectiveness of agriculture. In essence we strive to enhance our comprehension of crop behaviors enabling decision making, in agricultural and land management strategies.

PROPOSED SYSTEM CONFIGURATION

In our analysis of crop mapping using a series of satellite images over time we decided to use the UNET architecture, which's well known for its effectiveness, in tasks related to segmentation. We chose UNET because it excels at capturing features while also understanding changes over time within the dataset. Originally created by Olaf Ronneberger and his team in 2015 for segmenting images at the University of Freiburg in Germany UNET has now become an used method in various applications involving semantic segmentation.

The UNET architecture consists of two parts: the encoder and the decoder. The encoder comprises convolutional and pooling layers that extract features from the input data. On the hand the decoder uses upsampling and convolution operations to create a segmentation map based on the extracted features. This design is especially effective for analyzing aspects of satellite imagery while maintaining an understanding over time.

From a perspective we can express the convolution operation, in UNET as

$\mathbf{Y = W * X + b}$ where

Y - represents the output feature map

W -the weights of the kernel

X -the input feature map

b -bias term.

In networks the max pooling operation is commonly used for downsampling and can be expressed as

$\mathbf{Y[i,j] = max(X[2i:2i+2, 2j:2j+2])}$ Here

Y[i,j] -represents the pooled value at position (i, j) in the output

X -denotes the input feature map.

The rectified unit (ReLU) activation function, an element, in neural networks can be defined as Y = max(0, X). In this context Y indicates the result obtained after applying the ReLU function to the input X . Additionally UNET utilizes connections to transfer information from one network segment to another aiding in maintaining spatial details during upsampling. Mathematically speaking this process can be portrayed as Y = X where Y signifies the output of the connection and X represents the input transferred between network segments.

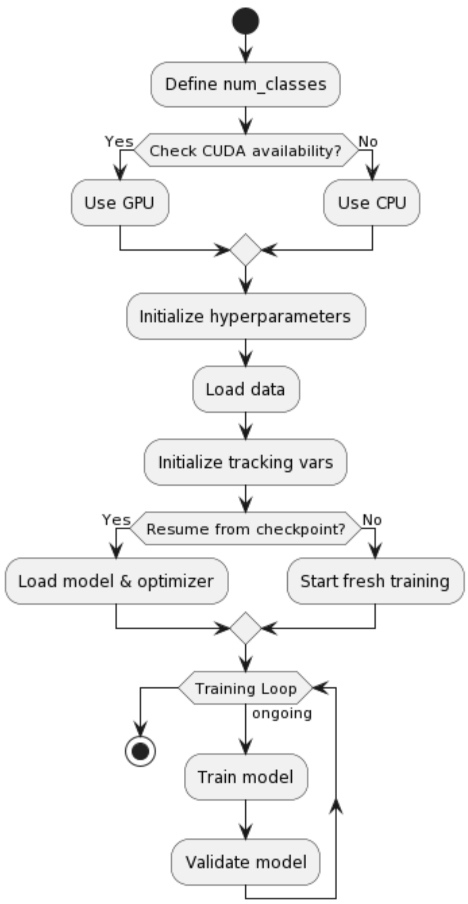

Fig.1 Image Showing the Architecture of the System

The following system consists of

Input Data: This part showcases the satellite image time series data utilized as input, for the crop mapping analysis carried out by the UNET model. It can be visualized as a rectangle labeled "Input Data."

UNET Model: This component embodies the architecture of the UNET, including the encoder and decoder layers for segmentation tasks. It can be depicted as a rectangle labeled "UNET Model."

Encoder Layers: These layers within the UNET model are in charge of extracting high level features from the input data through pooling operations. They serve as a sub component within the UNET Model rectangle.

Decoder Layers: The decoder layers in the UNET model are responsible for upsampling encoded features to create a segmentation map. They involve operations like upsampling and convolutions to encoder layers. Can also be represented as a sub component, within the UNET Model rectangle.

Output: This part symbolizes the segmentation map produced by the UNET model showcasing the distribution of crops. It can be represented as a rectangle labeled "Output."

```
print("Starting loading Dataset...")

traindataset = SentinelDataset(root_path, tileids="tileids/train_fold0.tileids", seqlength=sample_duration)
traindataloader = torch.utils.data.DataLoader(
    traindataset, batch_size=batch_size, shuffle=True, num_workers=workers)
# How to iterate on a dataloader
for iteration, data in enumerate(traindataloader):
    input, target, target_ndvi, _, _ = data
    print('input temporal series with 30 images of size 13x48x48:', input.shape)
    print('target segmentation image (batchx48x48):', target.shape)
    print('target_ndvi containing 30 channels of size 48x48:', target_ndvi.shape)
    break

# Load test set
testdataset = SentinelDataset(root_path, tileids="tileids/test_fold0.tileids", seqlength=sample_duration)
testdataloader = torch.utils.data.DataLoader(
    testdataset, batch_size=batch_size, shuffle=False, num_workers=workers)
# Load validation set
validationdataset = SentinelDataset(root_path, tileids="tileids/eval.tileids", seqlength=sample_duration)
validationdataloader = torch.utils.data.DataLoader(
    validationdataset, batch_size=batch_size, shuffle=False, num_workers=workers)

numclasses = len(traindataset.classes)
labels = list(range(numclasses))
```

```
Starting loading Dataset...

 rejected_nopath:3059, rejected_length:4778, total_samples:5231
input temporal series with 30 images of size 13x48x48: torch.Size([2, 13, 30, 48, 48])
target segmentation image (batchx48x48): torch.Size([2, 48, 48])
target_ndvi containing 30 channels of size 48x48: torch.Size([2, 30, 48, 48])

 rejected_nopath:890, rejected_length:1395, total_samples:1747

 rejected_nopath:806, rejected_length:1441, total_samples:1641
```

Fig.2 Data Loading

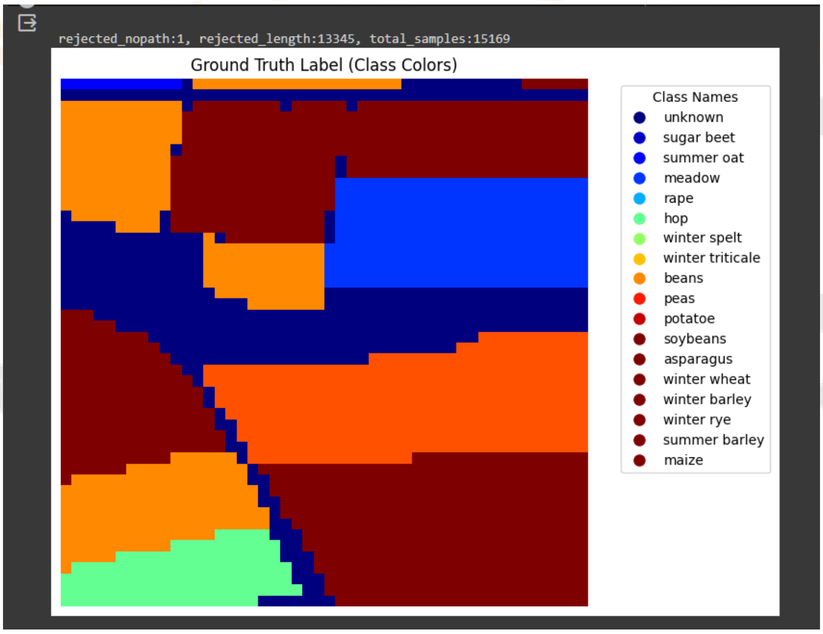

Fig.3 Ground Truth Visualization

```
#CONVOLUTIONAL KERNELS
%matplotlib inline

f, axs = plt.subplots(2,8,figsize=(15,4))
for i in range(16):
    axs.reshape(-1)[i].imshow(model_state["module.inconv.weight"][i,0,0])
```

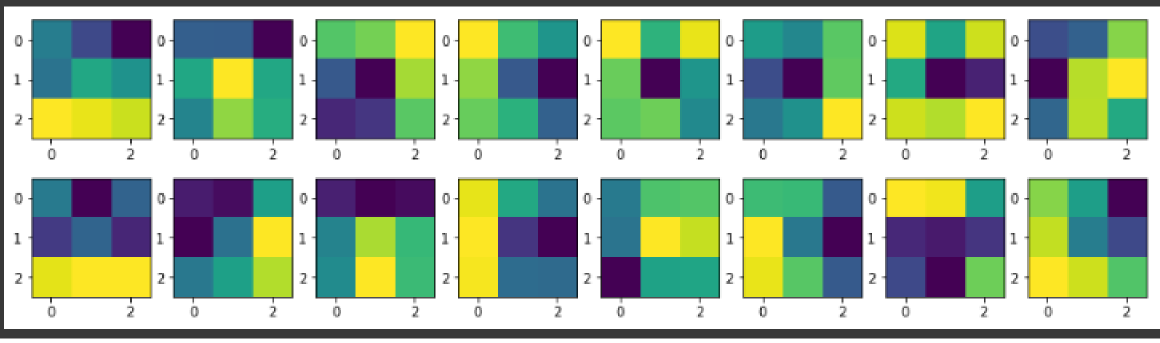

Fig.4 Convolution Kernels

```
f, axs = plt.subplots(3,6,figsize=(15,5))
for i in range(18):
    ax = axs.reshape(-1)[i]
    ax.imshow(activations[0,i])
    ax.set_axis_off()
    ax.set_title(dataset.classes[i])
```

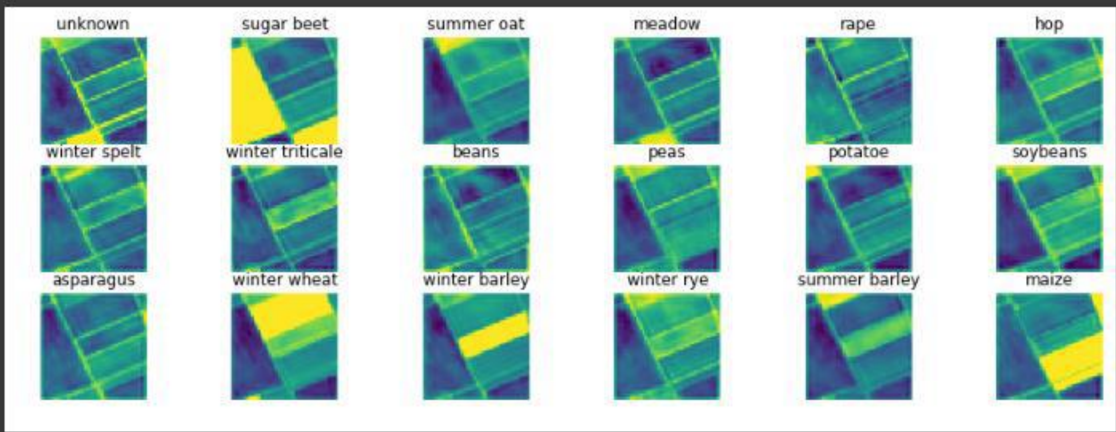

Fig.5 Class Wise Distribution

```
# GROUND TRUTH VS PREDICTION
f, axs = plt.subplots(1,2,figsize=(15,4))
axs[0].imshow(torch.squeeze(label)); axs[0].set_title("Ground Truth"); axs[0].set_axis_off()
axs[1].imshow(np.argmax(activations[0],axis=0)); axs[1].set_title("Prediction"); axs[0].set_axis_off()
```

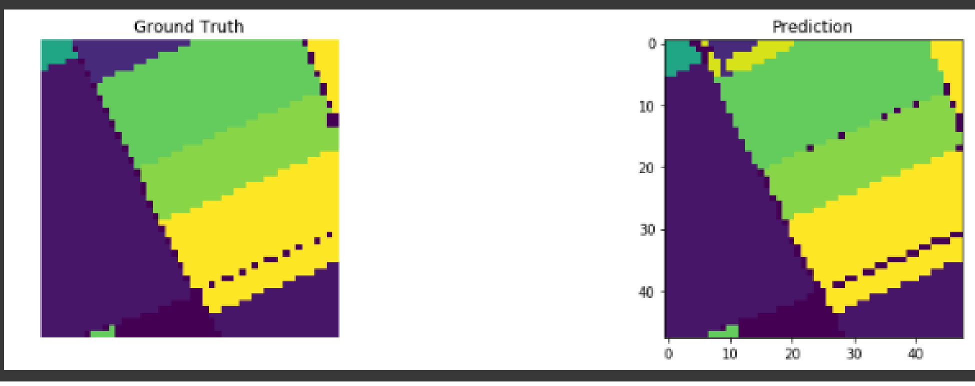

Fig.6 Ground Truth Vs Prediction

CONCLUSION

The design and execution phase of the project played a role, in shaping the models effectiveness resulting in an accuracy rate of 90.09% and notable enhancements in key performance indicators over the course of 31 training sessions. Despite facing obstacles the model showcased its flexibility and capacity to grasp patterns from the data ultimately delivering a reliable solution for the assigned task. Looking ahead opportunities to enhance the models performance exist through scrutinizing misclassifications exploring structures and tuning hyperparameters. The observed stabilization in training sessions indicates areas for exploration underscoring the projects potential for ongoing research and advancement. With a groundwork laid down this project acts as a stone for future improvements and applications across related fields offering promising advancements in crop mapping and, beyond.

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