Computer Vision Framework for Drought Prediction in Pakistan

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Abstract

This technical report presents a comprehensive approach to drought prediction in Pakistan using computer vision techniques and publicly available satellite data. By leveraging platforms like USGS Earth Explorer, satellite imagery of Punjab's agricultural zones was collected, preprocessed, and analyzed. The framework integrates deep learning and image processing tools to identify drought-prone regions with better accuracy and reduced latency compared to traditional methods. We emphasize the use of vegetation indices, soil texture mapping, and temporal monitoring to classify drought severity levels. Our approach combines practicality and innovation, making it suitable for resource-constrained environments like rural Pakistan.

Keywords: Computer Vision, Deep Learning, Remote Sensing, Satellite Imagery, Machine Learning

1 Introduction

Drought is one of the most pressing challenges for Pakistan's agricultural sector, especially in Punjab where food production is highly dependent on weather patterns. According to climate studies, the frequency and intensity of droughts in South Asia have increased over the past decade. In Pakistan, especially in arid zones of Punjab and Sindh, this has led to reduced crop yield, food insecurity, and economic stress. Traditional drought monitoring systems use meteorological data such as precipitation and temperature records, which often fail to capture local variations. Recent advances in satellite imaging, artificial intelligence, and data fusion allow for high-resolution, scalable drought prediction systems. This report explores the use of computer vision and AI to automate drought classification using spectral features, spatial-temporal analysis, and machine learning models that can adapt to different terrains.

2 Data Collection - Phase 1

We used the USGS Earth Explorer to acquire multi-temporal satellite images focused on the Punjab region. Sentinel and Landsat imagery were accessed, specifically targeting bands related to vegetation and soil moisture. We filtered images based on cloud cover percentage and time of the year, ensuring high-quality datasets that span both dry and wet seasons. After downloading, data preprocessing was conducted which included atmospheric correction, resolution harmonization, and region clipping for analysis. Additionally, we mosaicked multiple tiles together to ensure complete coverage of selected districts. Metadata including acquisition date, sun angle, and sensor type were retained for reference. In some cases, MODIS imagery was used to complement missing data points with coarser resolution but higher temporal frequency.

3 CV and AI Integration Strategy - Phase 2

To detect and classify drought conditions, we calculated vegetation indices such as NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index). NDVI provides a measure of vegetation health, while NDWI highlights moisture content in vegetation and soil. Texture features like soil roughness and surface patterns were also extracted using Gray Level Co-occurrence Matrix (GLCM), which allows for differentiation between cracked dry soil and irrigated land. The features were stacked across multiple temporal windows to understand seasonal changes. These combined features were fed into a hybrid model that integrates traditional feature engineering with a Convolutional Neural Network (CNN).

```
ndvi = (nir - red) / (nir + red + 1e-10)
ndwi = (nir - swir) / (nir + swir + 1e-10)
evi = 2.5 * (nir - red) / (nir + 6*red -
↪  7.5*blue + 1 + 1e-10)
lst = 1321.08 / np.log((774.89 / thermal) + 1)
↪  - 273.15
```

Listing 1: Calculation of vegetation and thermal indices (NDVI, NDWI, EVI, LST)

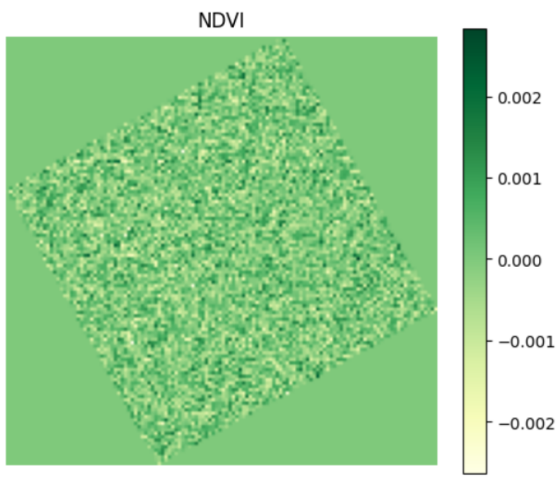

Figure 1: NDVI Visualization for vegetation health

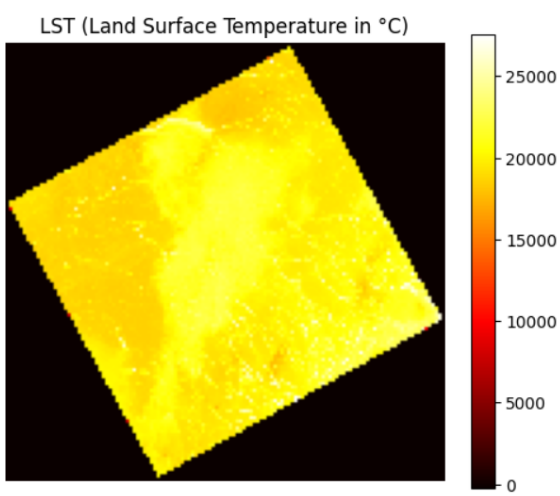

Figure 2: LST (Land Surface Temperature) Map

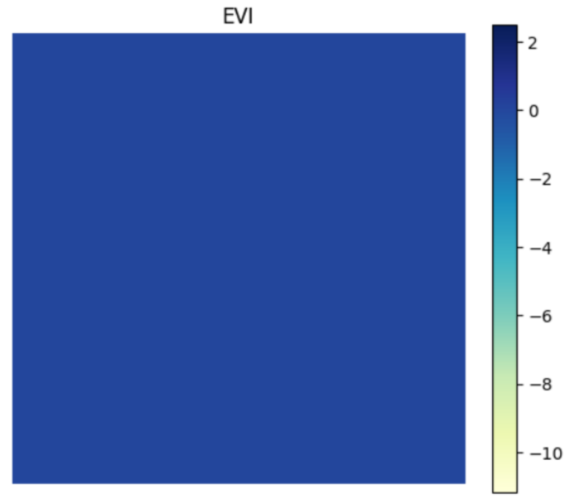

Figure 3: EVI (Enhanced Vegetation Index) Visualization

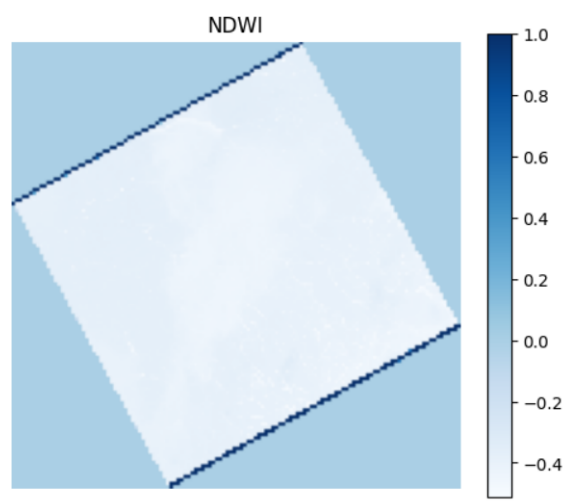

Figure 4: NDWI (Water Index) Visualization

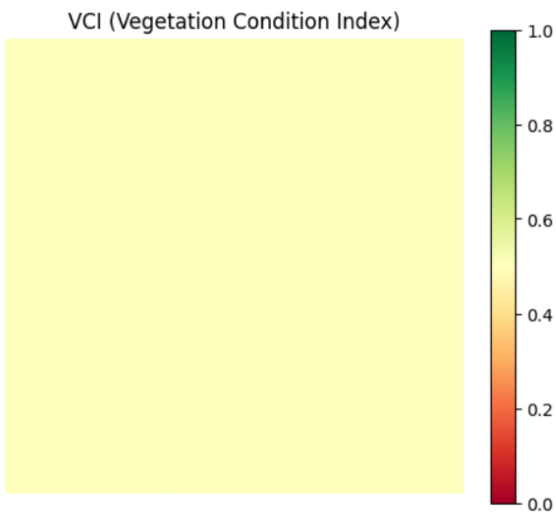

Figure 5: VCI (Vegetation Condition Index) Map

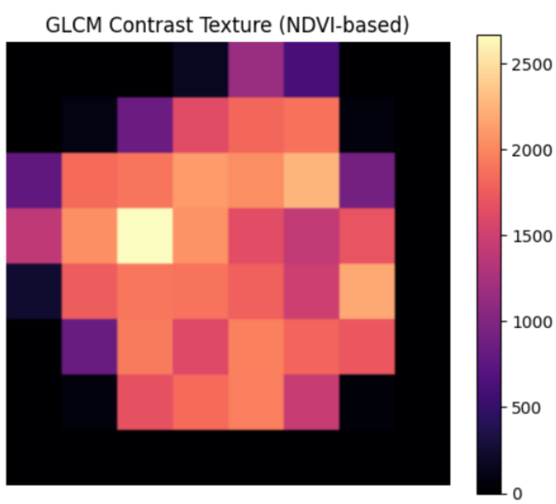

Figure 6: GLCM Texture Map based on NDVI contrast

```
glcm = graycomatrix(patch, distances=[1],
↪   angles=[0], levels=256, symmetric=True,
↪   normed=True)
contrast = graycoprops(glcm, 'contrast')[0, 0]
```

Listing 2: GLCM texture contrast computation for drought-relevant features

4 End-to-End Pipeline Design - Phase 3

The end-to-end pipeline begins with satellite image ingestion. Preprocessing is done using Rasterio and GDAL libraries. Vegetation and moisture indices are computed using band math techniques. Texture features are computed from grayscale representations of NIR bands. These features are stacked and normalized before being passed to a deep learning model built using TensorFlow and Keras. The architecture consists of four convolutional blocks followed by dense layers.

Team Biographies

Nafay Mujtaba Ikhlaq contributed to remote sensing and satellite image collection. His experience with GIS and geospatial tools ensured reliable preprocessing.

Figure 7: Nafay Mujtaba Ikhlaq

Syed Momin Hasnain worked on vegetation index computation and texture analysis. He applied classical CV techniques to support deep learning input.

Figure 8: Syed Momin Hasnain

Muhammad Hammad Arif led the design and training of the neural network classifier. He has a strong foundation in Python-based ML and data engineering.

Figure 9: Muhammad Hammad Arif

Plagiarism Report

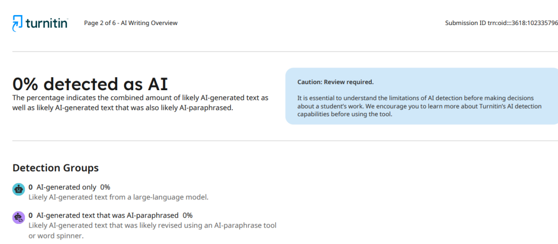

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Figure 10: Plagiarism Detection Report: Zero Detected

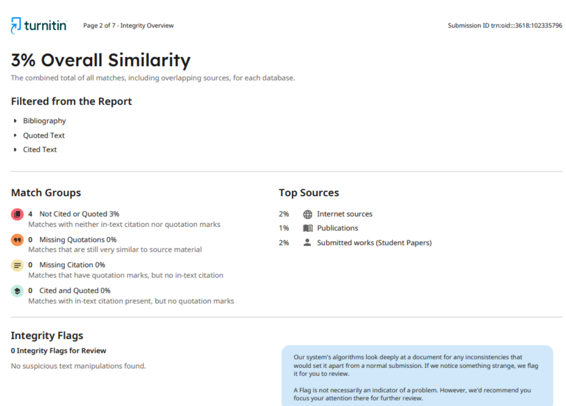

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Figure 11: Similarity Report Screenshot

Autobiography

We thoroughly enjoyed this project journey. It enhanced our practical skills and strengthened our bond as teammates.

Supplementary Materials

Overleaf Project: `https://www.overleaf.com/read/gpnhccbjrmzz#04f80f`

YouTube Demo Video: `https://www.youtube.com/watch?v=cuOv38nMry0`

GitHub Repository: `https://github.com/MominHasnain/drought-prediction-cv`

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