COMPUTER VISION TASKS

PROBLEM STATEMENT 1:

Provided with a satellite image of a study area, your task is to segment the image, and extract features such as wells and farm boundaries etc, from the image. How would you approach this task? What methods or techniques would you use to accomplish it? Develop a model to accomplish this task. Outputs should be vectors(shapefiles) of the features.

SOLUTION:

Wells Detection :

.1. preprocess images and extract useful information from segmented regions.

FUNCTIONS:

- load_image
- resize_image
- normalize_image
- enhance_contrast
- image_segmentation
- extract_featuures_for_segmentation

2. Normalized the data using Z-Score function

3. Loaded the satellite image(TIF file)

4. Image Preprocessing, Segmentation, and Feature Extraction Pipeline
   - **Preprocessing**: An image is loaded from the provided file path, resized to a target size, contrast is enhanced, and then pixel values are normalized to the range [0, 1].
   - **Image Segmentation**: The normalized image is segmented using the SLIC algorithm into a specified number of segments.
   - **Feature Extraction**: Features (mean color, std color, area, and perimeter) are extracted for each segmented region, and the results are stored in a DataFrame called `feature_df`
   - **Normalization of Raster Data**: The pixel values of each band in the raster data (satellite image) are z-score normalized.

- **Save Normalized Data**: The normalized raster data is saved to a new raster file named `normalized_raster.tif` with the appropriate metadata.

5. Circle Detection from Normalized Raster Image
    - **Loading and Preprocessing**: The normalized raster image is loaded using rasterio. A specific band is chosen, and its pixel values are converted to grayscale. Contrast enhancement is applied using the histogram equalization technique.
    - **Edge Detection**: The Sobel operator is applied to detect edges in the equalized band data. The gradient magnitude of the edges is calculated.
    - **Circle Detection**: The Hough Circle Transform is utilized to detect circles in the edge-detected image. A range of circle radii is defined, and the Hough Transform is applied to find candidate circles.
    - **Prominent Circle Selection**: The most prominent circles are selected based on the Hough Transform results. The center coordinates (cx and cy) and radii of the detected circles are obtained.

6. Detection and Visualization of Wells in Satellite Image
    - **Create GeoDataFrame for Wells**: A geopandas GeoDataFrame is initialized to store the detected well locations (circles).
    - **Convert Pixel Coordinates to Geographical Coordinates**: The pixel coordinates of detected well centers (from the Hough Circle Transform) are converted to geographical coordinates
    - **Add Well Centers to GeoDataFrame**: For each detected well, a Point geometry is created representing the well center in the GeoDataFrame. Each well center is appended to the GeoDataFrame as a new row.
    - **Save GeoDataFrame as Shapefile**: The GeoDataFrame containing the well locations is saved as a shapefile for further analysis and visualization.

    <u>I used QGIS, a popular open-source GIS software, to visualize the shapefile.</u>

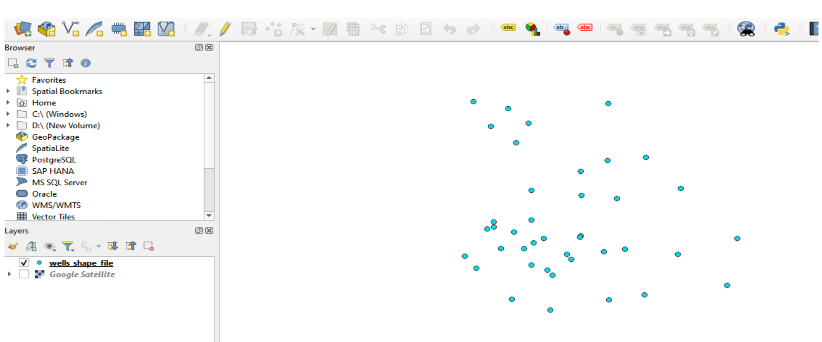


Fig 1: Shapefile Look

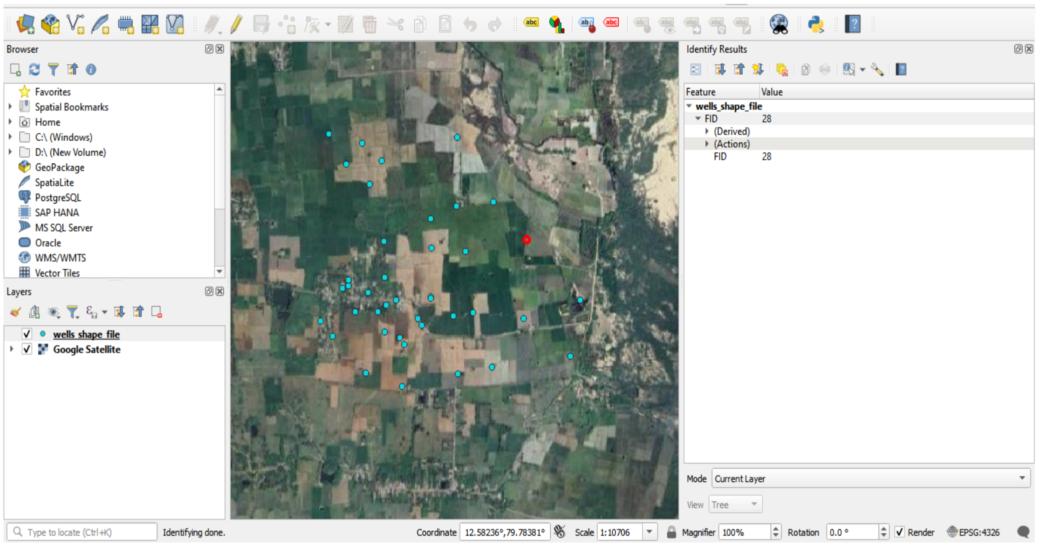


Fig 2: Shapefile on satellite image

The result confirms that the wells have been accurately detected on the satellite image. The "Identified Results" section on the right side displays the Feature ID (FID) when a well is selected or clicked, indicating the correct shapefile format.

<u>FARM BOUNDARIES DETECTION</u>:

Processes the satellite image, detects farm boundaries, and saves them as a shapefile

- **Preprocessing**: The satellite image is loaded using rasterio and preprocessed to enhance contrast. It is converted to grayscale and the contrast is further enhanced using histogram equalization.
- **Edge Detection**: Canny edge detector is applied to the preprocessed image to detect edges, which highlight boundaries in the image.
- **Contour Detection**: Contours are found from the binary edges obtained through Canny edge detection.
- **Filtering and Polygon Extraction**: Contours with too few points are filtered out, and the remaining contours are converted into polygons to represent the farm boundaries.
- **Save Farm Boundaries as Shapefile**: The detected farm boundaries in the form of polygons are saved as a shapefile for further analysis and visualization.

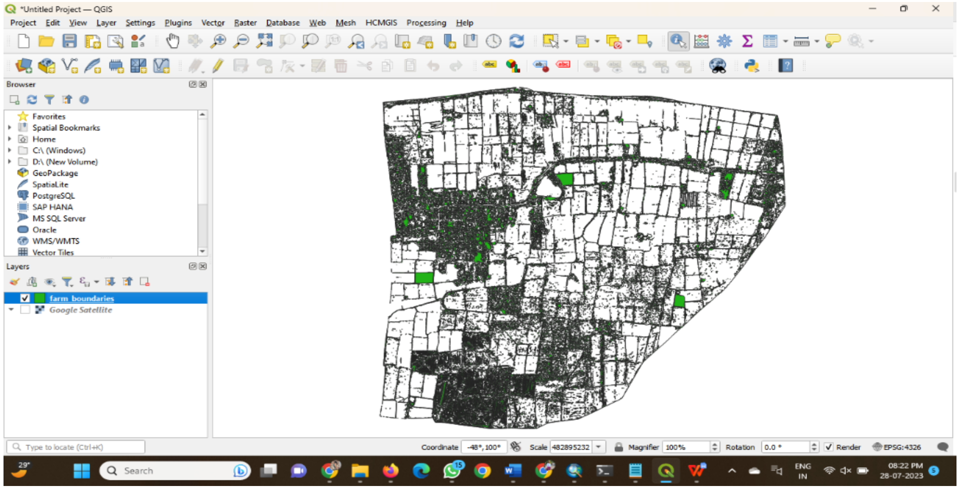
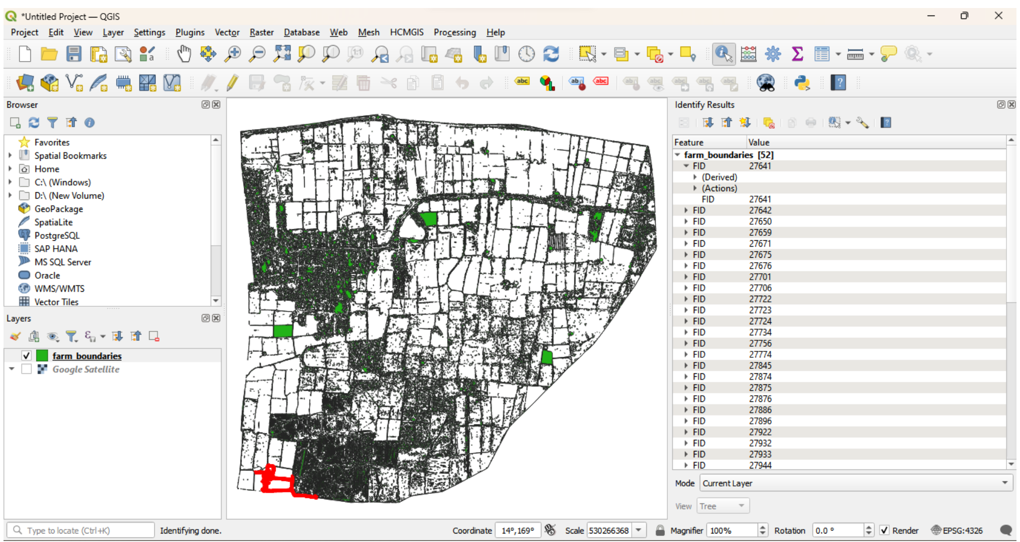


Fig 3: shapefile for Farm Boundaries



The result confirms that the farm boundaries have been accurately extracted on the satellite image. The "Identified Results" section on the right side displays the Feature ID (FID) when a well is selected or clicked, indicating the correct shapefile format.

PROBLEM STATEMENT 2:

Provided with a drone image of a study area, your task is to extract building footprints from the image. How would you approach this task? What methods or techniques would you use to accomplish it? Develop a model to accomplish this task. Outputs should be vectors(shapefiles) of each feature.

SOLUTION:

Building Footprint Extraction from Aerial Images using Mean Shift Clustering

Data Preprocessing:

- Load the aerial image and resize it to a desired width and height.
- Convert the image to a NumPy array for further processing.
- Flatten the image to prepare it for K-Means clustering.

Image Segmentation:

- Perform Mean Shift clustering on the flattened image to identify clusters of similar pixels representing building regions.
- Reshape the clustered labels back to the original image dimensions to create the segmented image.

Building Footprint Extraction:

- Extract geometries (polygons) of individual clusters from the segmented image.
- Create a GeoDataFrame to store the building footprints' geometries.
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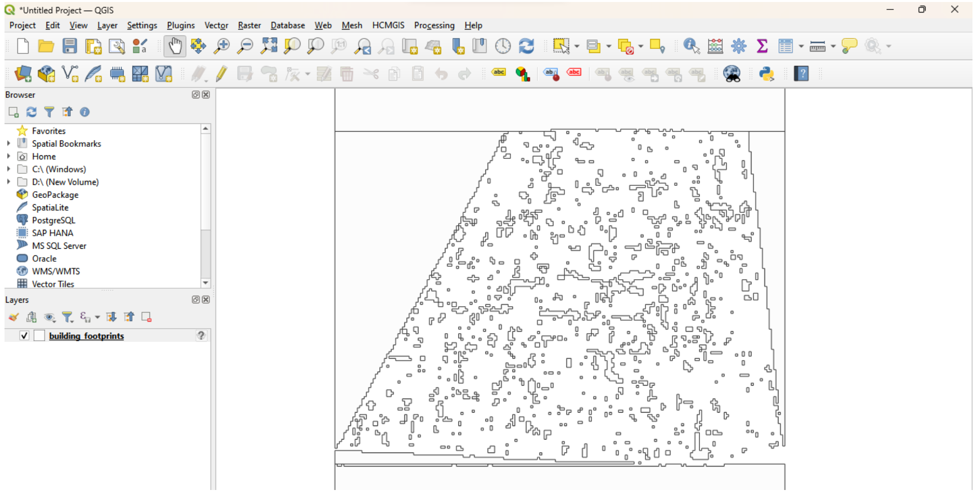
Visualization:

- Visualize the segmented image with different clusters shown in distinct colors using a color map.
- Display the building footprints overlaid on the original aerial image using the GeoDataFrame.



The implemented method using Mean Shift clustering effectively identifies and extracts building footprints from aerial images.

PROBLEM STATEMENT 3:

Develop a deep learning image classification model using Python (or any programming language of your choice) to classify the type of pest disease affecting the paddy rice crop. The model should take input images of the affected paddy rice leaves and accurately predict the specific type of pest disease causing the damage.

SOLUTION:

The developed deep learning image classification model proves to be a valuable tool for early detection and classification of pest diseases in paddy rice crops.

- **Preprocessing**: The images are preprocessed by converting them to grayscale, enhancing contrast, and resizing them to a fixed size of 128x128 pixels.
- **Data Augmentation**: Data augmentation is applied to increase the diversity of the training dataset. Techniques like rotation, width and height shift, shear, zoom, and horizontal flip are used to create variations of the original images.
- **Base Model**: The VGG16 model is used as the base model without the top (classification) layers.
- **Custom Classification Layers**: Custom classification layers are added on top of the base model, including a flatten layer, a dense layer with 256 units and ReLU activation, a dropout layer with 50% dropout rate, and a dense layer with softmax activation for multi-class classification.

- **Transfer Learning**: The base model's layers are frozen to prevent overfitting, and only the custom classification layers are trainable.
- **Model Training**: The model is compiled using the Adam optimizer and categorical cross-entropy loss. It is then trained on the augmented training data with a batch size of 32 and 20 epochs.
- **Evaluation**: The model's performance is evaluated on the test set using accuracy as the metric. The test accuracy is recorded to assess the model's ability to classify the different pest diseases accurately.

```
1/1 [==============================] - 4s 4s/step - loss: 0.3059 - accuracy: 0.9167
Test accuracy: 0.9166666865348816
```

The model achieves a high accuracy on the test set, demonstrating its effectiveness in accurately classifying the specific type of pest disease affecting the paddy rice crops.