

An aerial photograph of a winding asphalt road that curves through a dense, green forest. The road is light gray and contrasts with the dark green trees. The forest appears to be a mix of deciduous and coniferous trees. The road starts from the bottom left and winds upwards and to the right, disappearing into the trees in the distance. The overall scene is a natural, scenic landscape.

Land Use Classification

Xue Ming Wang (Vivian)

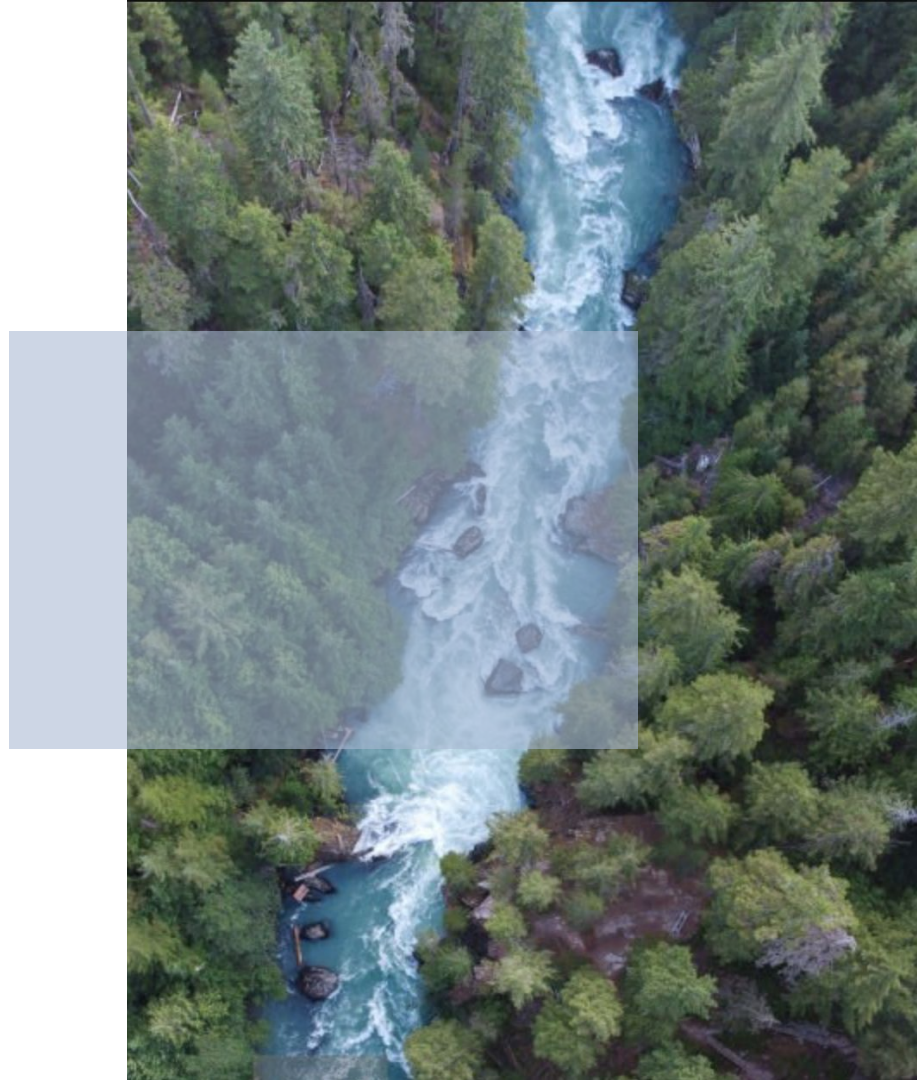
Github Link:

<https://github.com/Xue-Ming-Wang/6289-Midterm.git>

Background

Aerial imagery of land use captures Earth's surface from above. With technology like drones and AI, it's now more accessible and efficient, crucial for decision-making in different fields.

Applying machine learning enhances land use management and decision-making, particularly in urban planning and environmental monitoring.






Motivation

Aim to create a solution for automated land use classification with real-world applications, such as:

- Monitoring land use changes
- Urban planning
- Resource management, etc.

An aerial photograph of a sprawling city, likely Hong Kong, showing a dense urban landscape with numerous skyscrapers and buildings. The city is situated along a coastline with a large harbor filled with ships. In the background, there are mountains partially covered in clouds. The sky is blue with scattered white clouds.

Goal: Develop a CNN model capable of classifying random aerial imagery of land use into different land use classes.

Dataset Description

Dataset:

UCMerced_LandUse

By University of California, Merced for land use classification

- Satellite images of 21 distinct land use
- Land use patterns around the UC, Merced campus
- From Google Earth and Google Maps

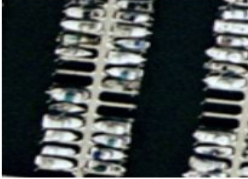


- 2,100 images, with 100 images per class
- In formats such as JPEG or PNG
- Mostly 256x256 pixels

Land Use Categories

Agricultural, Airplane, Baseball Diamond, Beach, Buildings, Chaparral, Dense Residential, Forest, Freeway, Golf Course, Harbor, Intersection, Medium Residential, Mobile home Park, Overpass, Parking Lot, River, Runway, Sparse Residential, Storage Tanks, and Tennis Court.

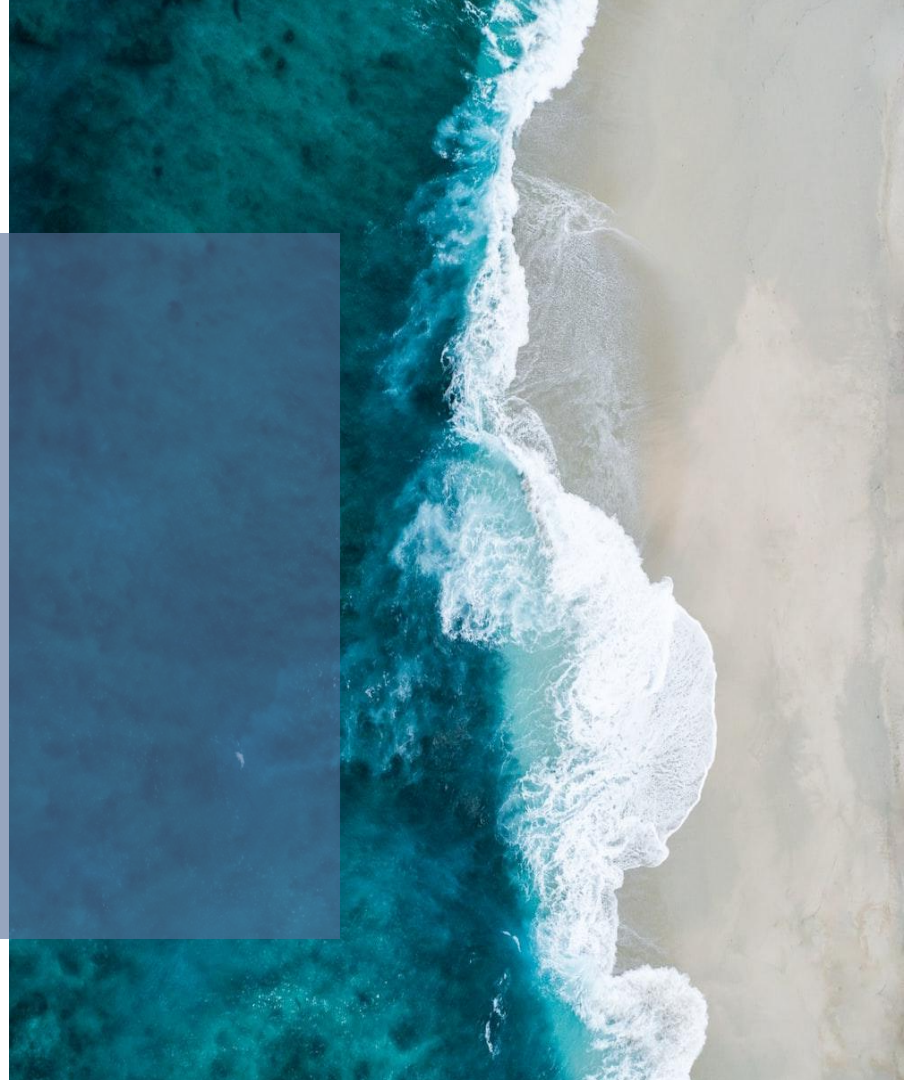
Dataset Examples

Dataset Link: https://www.tensorflow.org/datasets/catalog/uc_merced

	filename	image	label
0	harbor22.tif		10 (harbor)
1	tenniscourt86.tif		20 (tenniscourt)
2	freeway33.tif		8 (freeway)

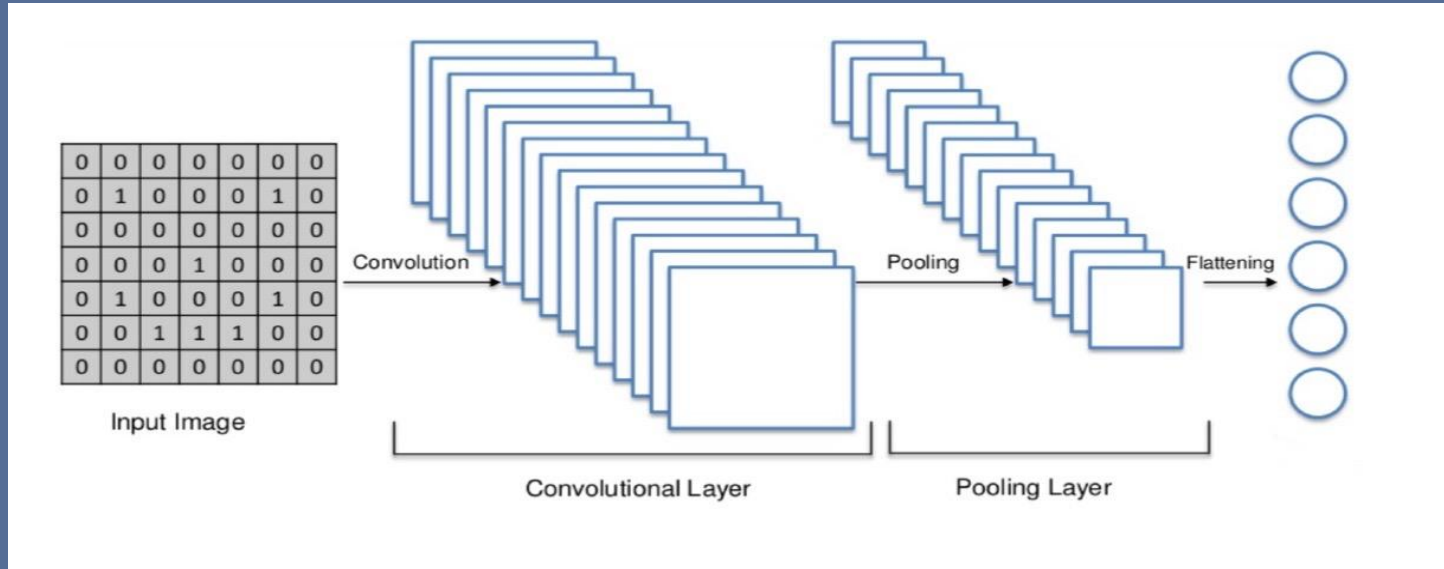
Preprocessing

- 70% for training set and 30% for test set, for model development and evaluation.
- Resized to a consistent 224x224 pixel dimension.
- Normalizing pixel values to $[0, 1]$ enhances training stability.



CNN Model

- Convolutional layers to identify local features
- Max-pooling layers to reduce dimensionality
- Flattened the output to prepare the data for the fully connected layers



My CNN Model

Sequential Model:

- 1st Layer: 2D with 64 filters with ReLU (Rectified Linear Unit) activation function
- MaxPooling2D layer (2x2 pooling window)
- 2nd Layer: 2D with 128 filters
- MaxPooling2D layer
- 3rd Layer: 2D with 256 filters
- MaxPooling2D layer
- Flatten Layer
- 1st Dense layer: 256 units with ReLU activation
- Dropout layer: Rate of 0.5 for regularization
- Final Dense layer: 21 units with a softmax activation

Compilation:

- Compiled with the Adam optimizer
- Used sparse categorical cross-entropy loss

```
# Define CNN model
model = keras.Sequential([
    layers.Conv2D(64, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    layers.MaxPooling2D((2, 2)),

    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),

    layers.Conv2D(256, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),

    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(21, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Train and validate the model

Train with

`model.fit`

Set epochs

`= 50`

Batch size

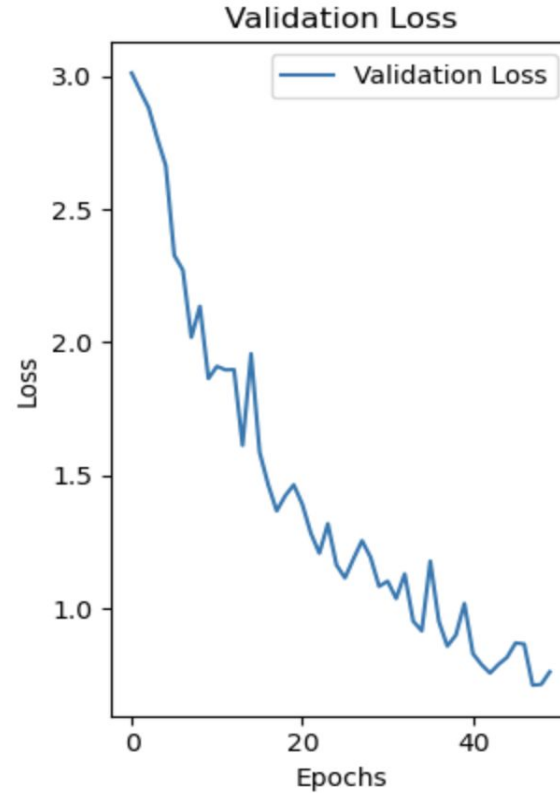
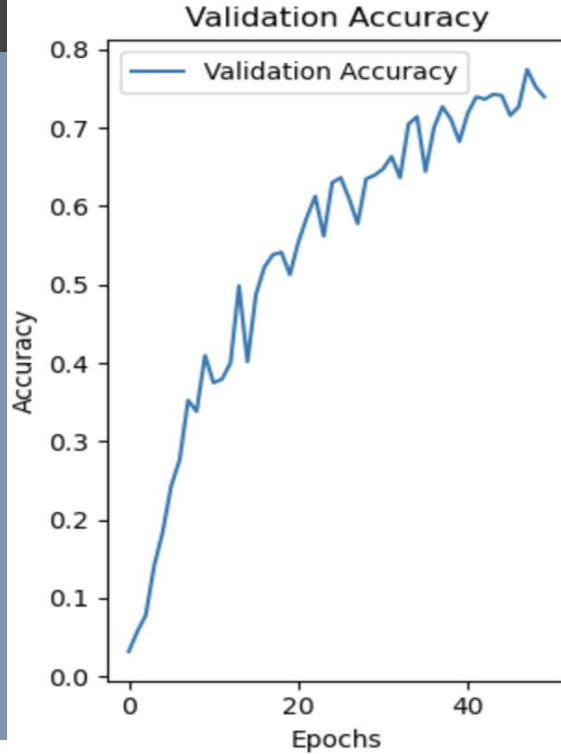
`= 32`

* Applied data augmentation with ImageDataGenerator to the training images to improve generalization

*Used early stopping for regularization

Accuracy

* Overfitting Problem



Test accuracy: 0.7396825551986694

Further Improvements



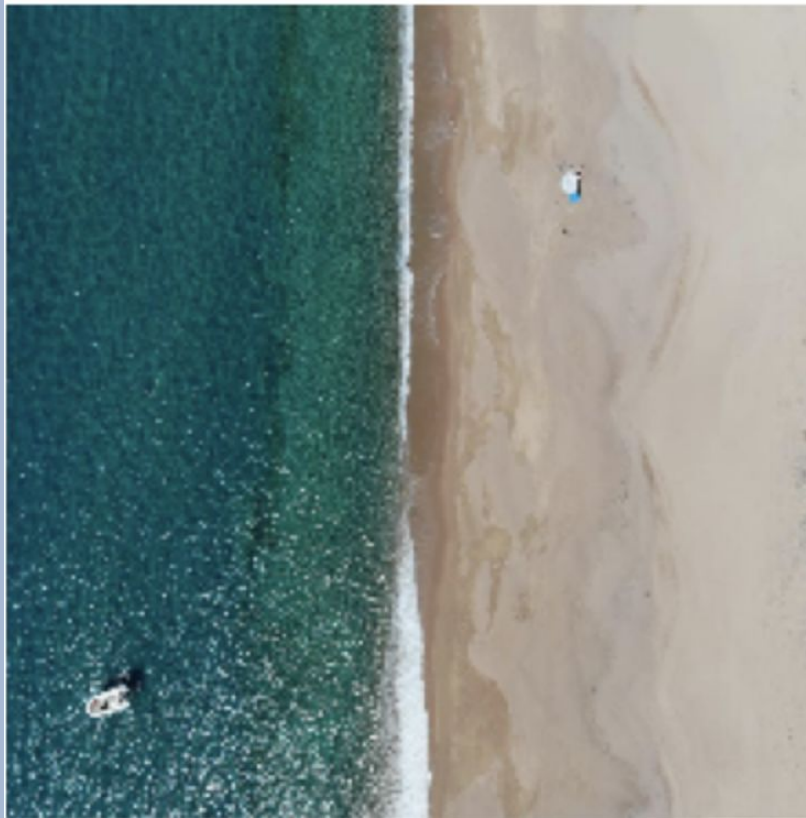
1. Construct a more complex model with additional layers or use a larger training dataset



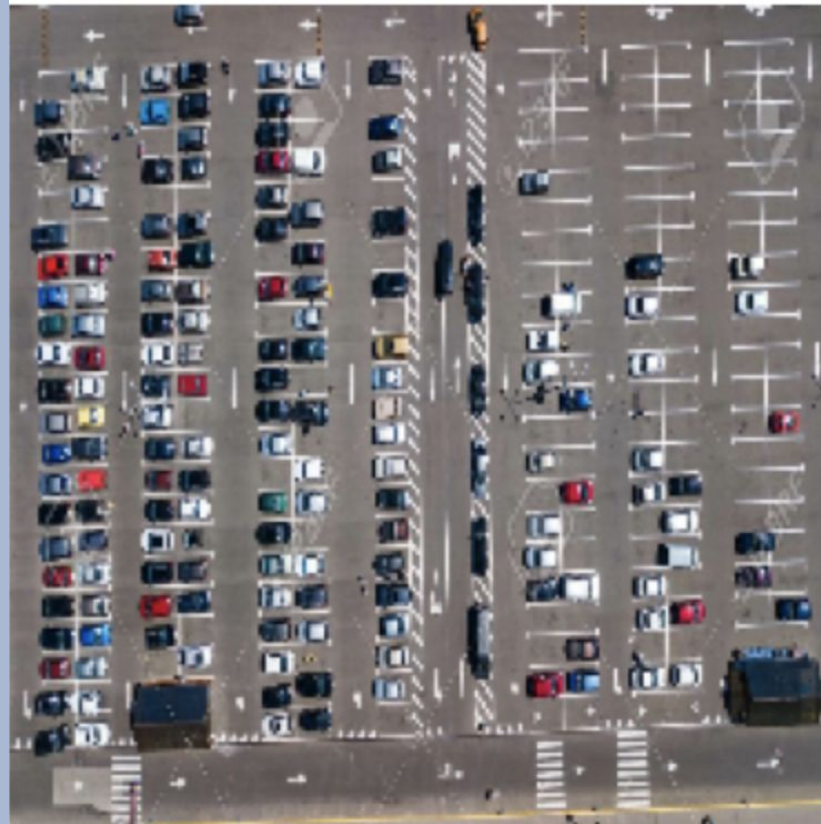
2. Generate a confusion matrix to identify specific misclassifications

Sample Predictions

Predicted Class Label: beach



Predicted Class Label: parkinglot



Summary

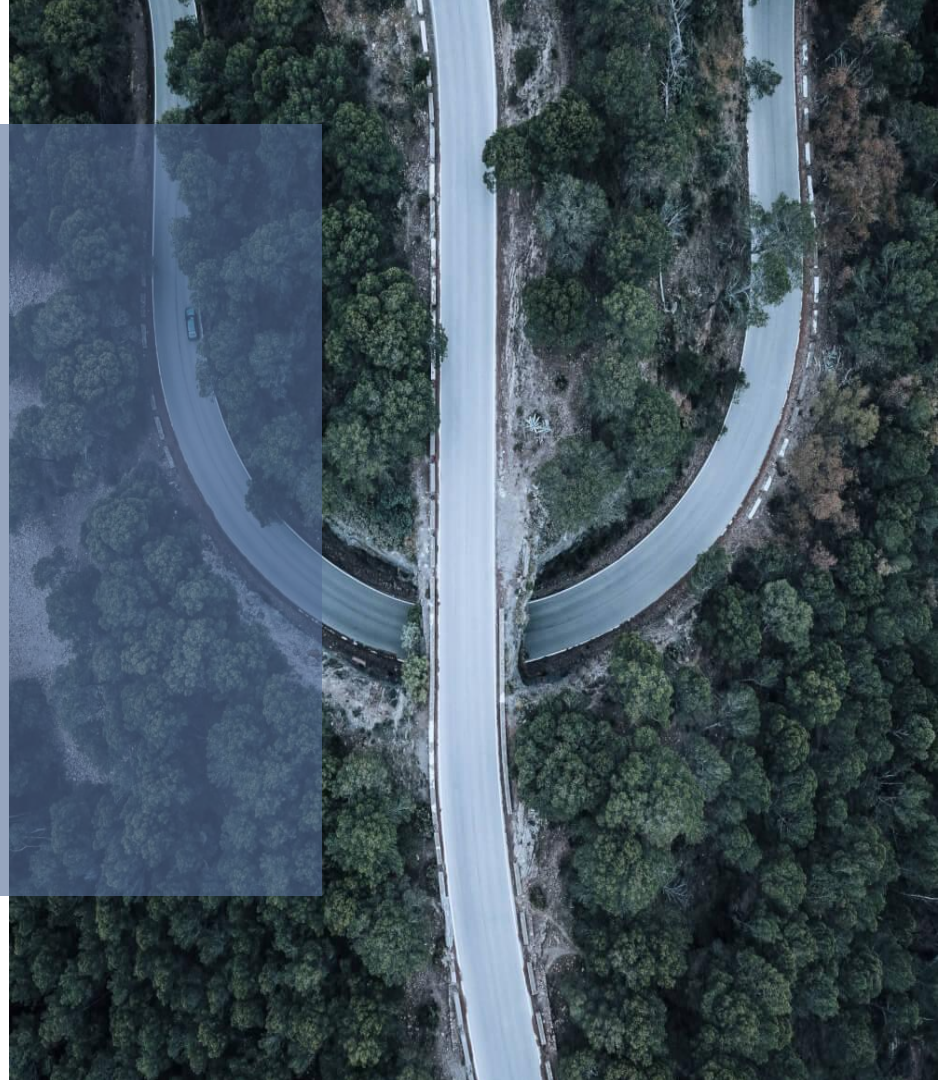
I achieved 73.96% accuracy in random aerial imagery of land use classification using my CNN model.

This model could be applied to:

- Urban Planning
- Resource Management
- Providing valuable insights for decision-making in multiple fields, including agriculture, disaster management, and more.

Github Link:

<https://github.com/Xue-Ming-Wang/6289-Midterm.git>



References

Jin , Fang. "Homework2-cifar10_cnn_py." Tensor-beginning, GitHub repository.
https://github.com/fangjin/STAT6289/blob/main/Tensor-beginning/cifar10_cnn_py.ipynb

Dataset: Yang, Yi and Newsam, Shawn. "Bag-Of-Visual-Words and Spatial Extensions for Land-Use Classification." In ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS), 2010.

Sample Image 1-2 References:

1. https://www.reddit.com/r/itookapicture/comments/cryxmd/itap_of_a_beach_from_the_sky/
2. https://www.123rf.com/photo_84174916_aerial-top-view-of-parking-lot-with-many-cars-from-above-transportation-and-urban-concept.html