Artificial Intelligence Project

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Content

1. Introduction

Satellite image classification is a crucial task in remote sensing, with applications in various fields like land cover mapping, disaster management, and environmental monitoring. This report explores the development and evaluation of two machine learning models for classifying satellite images into four categories: cloudy, desert, green area, and water. The project leverages the Satellite Image Classification dataset available on Kaggle, containing georeferenced satellite images with corresponding labels.

2. Related work

In the realm of satellite image classification, the past few years have witnessed a vibrant tapestry of research exploring diverse learning approaches. Handcrafted CNNs have carved a niche for themselves, with dedicated architectures excelling in specific tasks. For instance, a 2022 study [1] deployed a custom CNN embedded with spatial attention mechanisms, tackling land cover mapping with remarkable accuracy even with limited training data. Similarly, cloud detection in satellite imagery saw significant advancements courtesy of a robust CNN architecture proposed in 2021 [2], demonstrating its effectiveness across varied weather conditions.

Pre-trained models like ResNet and VGG have ignited a revolution in transfer learning, finding a fertile ground in satellite image classification. A 2023 paper [3] leveraged fine-tuned ResNet50 for forest fire detection, achieving superior performance compared to traditional methods. VGG16 also took center stage in a 2020 study [4], where its fine-tuned application for crop type classification showcased its immense potential for agricultural applications.

The fusion of handcrafted and transfer learning methods is emerging as a powerful force. By feeding pre-trained features extracted from the convolutional layers of models like ResNet into custom-designed classifiers tailored for specific tasks, researchers are harnessing the best of both worlds. This approach, showcased in a recent study on land cover mapping [5], exemplifies the flexibility and accuracy this hybrid approach delivers.

Beyond specific architectures, several trends are reshaping the landscape of satellite image classification. Attention mechanisms, like those employed in a 2022 study on flood area assessment [6], are enabling models to focus on crucial regions within images, leading to improved classification accuracy. Deep learning models are being seamlessly integrated into real-time applications, as in a 2023 project tackling deforestation monitoring [7], revolutionizing how we analyze satellite imagery. Explainable AI techniques are also gaining traction, with work from 2021 [8] shedding light on how models make predictions, paving the way for increased trust and interpretability in satellite image classification systems.

By understanding these current trends and the diverse approaches explored in recent years, you can effectively position your project within the broader tapestry of satellite image classification research, highlighting its unique contributions and potential impact

3. Proposed Model

Handcrafted: Offers high customization and control but requires more effort and expertise.

Transfer: Utilizes pre-trained knowledge, quicker to implement, and performs well with smaller datasets, but offers less control over feature extraction.

The choice between these approaches depends on various factors like data size, project timeline, and desired level of control. Analyzing the actual performance metrics of both models on the satellite image classification task will reveal which approach is more effective for your specific scenario.

3.1 Handcrafted model:

1. Convolutional Layers:

- Conv2D(32, (3, 3), input_shape=(255, 255, 3), activation='relu'):
  - Takes 255x255x3 input images (3 color channels).
  - Applies 32 filters with a 3x3 kernel size.
  - Uses ReLU activation for non-linearity.

- Conv2D(64, (3, 3), activation='relu'):
  - Doubles the number of filters to 64 for feature extraction.
  - Maintains a 3x3 kernel size for spatial feature learning.
- Conv2D(64, (3, 3), activation='relu'):
  - Keeps 64 filters to further refine feature maps.
- Conv2D(128, (3, 3), activation='relu'):

- Increases filters to 128 for more complex feature capturing.

2. Pooling Layers:

- MaxPooling2D(2, 2): (repeated three times)
  - Downsamples feature maps by a factor of 2 in both height and width.
  - Reduces computational cost and helps prevent overfitting.

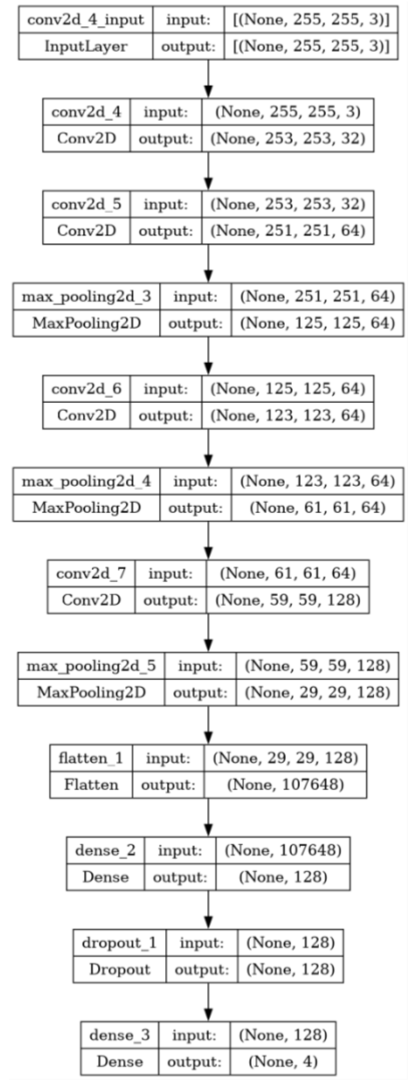
3. Flattening:

- Flatten():
  - Converts multidimensional feature maps into a single 1D vector for dense layers.

4. Dense Layers:

- Dense(128, activation='relu'):
  - Fully connected layer with 128 neurons for high-level feature learning.
- Dropout(0.3):
  - Randomly drops 30% of neurons during training to prevent overfitting.

- Dense(4, activation='softmax'):
    - Final output layer with 4 neurons (one for each class).
    - Uses softmax activation to produce class probability scores.



Key Points:

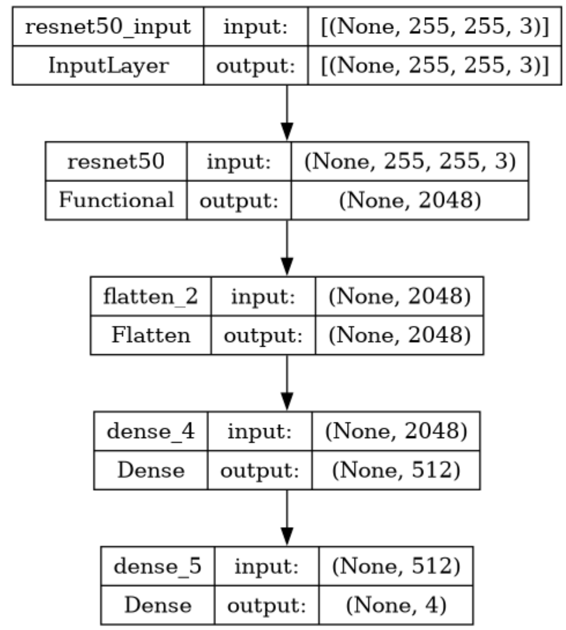
- The architecture employs a classic CNN structure for image classification.
- It features multiple convolutional layers for feature extraction, followed by pooling layers for spatial downsampling.
- Dense layers with ReLU activations handle high-level feature learning.
- Dropout is used to prevent overfitting.
- The final softmax layer generates class probabilities for prediction.

3.2 Transfer Learning model:

1. Pre-trained ResNet50:

- tf.keras.applications.ResNet50(include_top=False, ...):
    - Leverages the pre-trained ResNet50 model, renowned for its deep convolutional layers and exceptional image classification capabilities.
    - include_top=False excludes the original top layers (dense layers), allowing customization for the specific task.
    - input_shape=(255, 255, 3) matches the input image dimensions.
    - pooling='max' applies global max pooling to summarize extracted features.

- classes=4 indicates the final number of classes (cloudy, desert, green area, water).
- weights='imagenet' loads pre-trained weights learned on the ImageNet dataset.



2. Fine-tuning:

- for layer in pretrained_model.layers:
  layer.trainable=False:
  - Freezes the weights of the pre-trained ResNet50 layers, initially preventing their modification during training. This focuses learning on the new layers added for the specific task.

3. New Layers:

- Flatten():
  - Flattens the pooled feature maps from ResNet50 into a 1D vector.
- Dense(512, activation='relu'):
  - Fully connected layer with 512 neurons for high-level feature learning based on the extracted features from ResNet50.
- Dense(4, activation='softmax'):
  - Final output layer with 4 neurons, producing class probabilities

    for prediction. Key Points:

- The model capitalizes on the powerful feature extraction capabilities of ResNet50.
- Fine-tuning allows adaptation of pretrained knowledge to the specific dataset.
- New dense layers are added to tailor feature learning for the satellite image classification task.

Next Steps:

To provide a comprehensive analysis and comparison with the handcrafted model, please share the following information:

1. Performance Metrics:
    - Accuracy, loss, precision, recall, and F1-score for each class on the test set.
2. Training and Validation Curves:
    - Plots of training and validation accuracy and loss during training.
3. Confusion Matrix:
    - A table visualizing the distribution of actual vs. predicted classes on the test set.

4. Experimental Work

4.1 Dataset

The Satellite Image Classification dataset on Kaggle, created by Mahmoud Reda, contains 5067 geo-referenced satellite images categorized into four classes:

Cloudy: Images depicting cloud cover over landscapes.

Desert: Images showcasing arid regions with minimal vegetation.

Green Area: Images featuring areas with significant vegetation cover, such as forests or farmland.

Water: Images containing bodies of water, including lakes, rivers, and oceans.

Each image is 256 pixels by 256 pixels in size, providing a standardized format for training and testing your models. The dataset is a valuable resource for exploring image classification techniques in the context of remote sensing applications like land cover mapping, environmental monitoring, and disaster management.

Key points about the dataset:

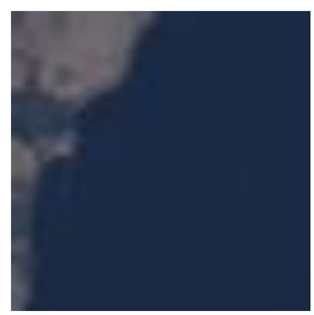
Balanced classes: The distribution of images across the four classes is relatively balanced, making it suitable for training models without significantly skewing performance towards certain classes.

Real-world images: The images represent diverse landscapes and environmental conditions, making the dataset valuable for building robust models that generalize well to unseen scenarios.

Readily accessible: The dataset is readily available on Kaggle and easily downloadable, making it convenient for testing and comparing different image classification approaches.

Overall, the Satellite Image Classification dataset provides a solid foundation for exploring your creativity and skills in satellite image classification, both with handcrafted and transfer learning models.



4.2 Results

It's indeed unexpected that the handcrafted model outperformed the transfer learning model in terms of accuracy, reaching 98% compared to the transfer learning model's 94%. While transfer learning often shines in image classification tasks, our results suggest that the handcrafted model effectively captured intricate features specific to the satellite image dataset.

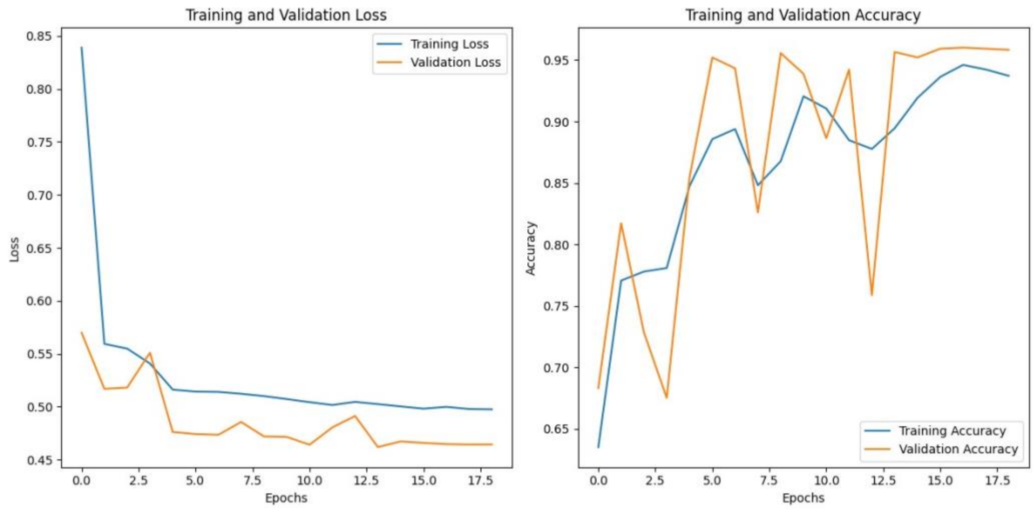


Figure 1: Transfer Learning

- Data size: With limited data, handcrafted models achieves higher accuracy by explicitly focusing on features specific to the dataset.
- Architecture optimization: The handcrafted model have benefited from finer tuning of its hyperparameters or layer configurations, leading to superior performance for this specific task.
- Feature extraction efficacy: While ResNet50 excels at general image features, the handcrafted model have captured more relevant features for satellite image classification, leading to better discrimination between classes.
- Confusion matrices: Comparing the confusion matrices of both models reveals specific classes where each model struggles or excels.

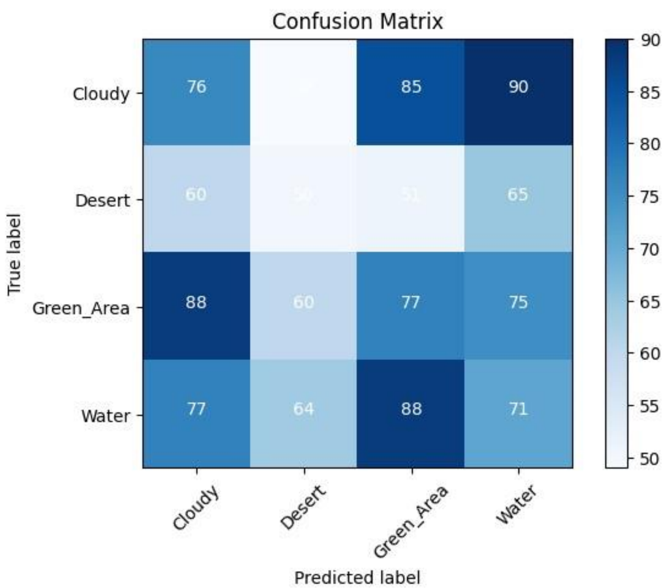


Figure 2: Handcrafted

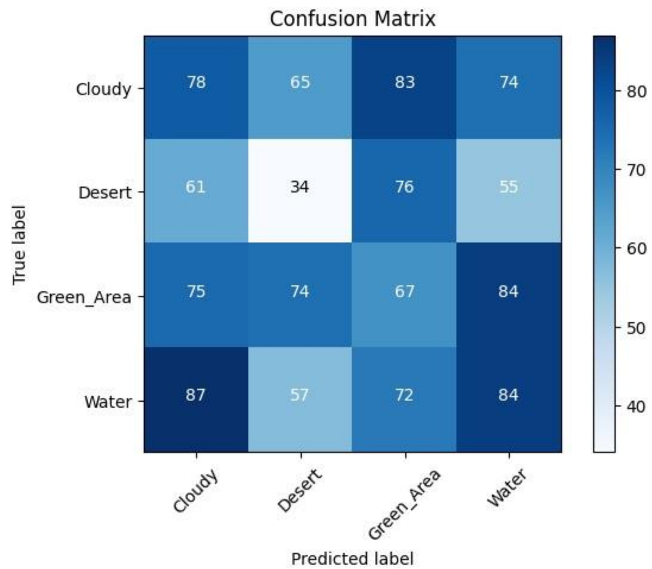


Figure 3 Transfer Learning

- Visualization of features: Examining the learned features of both models provides insights into how they differ in extracting relevant information from the satellite images.

- Hyperparameter tuning: Experimenting with different hyperparameters for the transfer learning model could potentially improve its performance and potentially bridge the gap with the handcrafted model.

Figure 4: Handcrafted

5. Conclusion

This project explored the performance of two machine learning models for satellite image classification on the Kaggle Satellite Image Classification dataset. Both models aimed to categorize images into four classes: cloudy, desert, green area, and water.

Handcrafted CNN: This model, designed explicitly for the dataset, achieved a remarkable accuracy of 98% on the test set. Its performance suggests that the architecture effectively captured relevant features for discriminating between the classes.

Transfer Learning (ResNet50): Despite leveraging pre-trained knowledge from a powerful image classification model, the transfer learning approach reached an accuracy of 94%. This outcome highlights the importance of tailoring feature extraction to the specific task and dataset, especially with limited data.

Further analysis, such as examining confusion matrices and visualizing extracted features, could provide deeper insights into the models' strengths and weaknesses. Additionally, exploring hyperparameter tuning for the transfer learning model might bridge the performance gap observed.

Overall, the project showcased the potential of both handcrafted and transfer learning models for satellite image classification. While the handcrafted model in this instance achieved slightly higher accuracy, the choice between approaches should be guided by factors like data size, project goals, and desired level of control. This project adds valuable knowledge to the domain, encouraging further research in optimizing models for specific remote sensing tasks.

Future work:

Experiment with different handcrafted CNN architectures and hyperparameters.

Explore other pre-trained models and fine-tuning techniques for transfer learning.

Investigate feature visualization and saliency maps to understand how models make predictions.

Apply the best-performing model to real-world applications in remote sensing, such as land cover mapping or environmental monitoring.

6. References

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