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Satellite-Based Land Cover Mapping Through Fine-Tuned ResNet-50 Architecture

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Abstract : **Land use and land cover (LULC) classification is important to monitor environmental changes and efficiently manage natural resources. This study uses a deep learning approach with the ResNet-50 architecture, pre-trained on the ImageNet database, to classify satellite images of the EuroSAT dataset into ten distinct land cover categories. The classification is based entirely on RGB bands, with the performance of the model enhanced further through data augmentation methods. With the trained model, high accuracy is obtained, with the ability to distinguish between land cover classes like forests, urban settlements, and agricultural lands. These outcomes show the tremendous potential of transfer learning in remote sensing and satellite image analysis.**

IndexTerms **- Land Cover Classification, ResNet-50 Architecture, EuroSAT Dataset, Deep Learning Techniques, Remote Sensing Applications.**

I. INTRODUCTION

Land cover classification play an important role in remote sensing, with applications ranging from environmental management to urban planning, agriculture, and disaster response. Proper classification of land cover categories such as forests, urban, water bodies, and agricultural areas is crucial for land type identification, environmental impact assessment, and decision-making on resource management. Conventional methods such as maximum likelihood classification and support vector machines (SVM) are typical for this purpose. These approaches fail with high-resolution images because they rely on extracting features and cannot express intricate spatial relations in the data.

With the evolution of deep learning, convolutional neural networks (CNNs) have revolutionized image classification, allowing automatic feature extraction from raw data. CNNs are particularly adept at detecting hierarchical patterns and spatial relationships in images, which is especially suited to land cover classification of satellite and aerial imagery. Out of all CNN models, ResNet-50, which is a deep residual network, has proven immense success in image recognition applications through the utilization of residual connections, which counteract the vanishing gradient issue. This makes it efficient in learning from deeper layers without performance diminishment, leading to recognizing complex patterns and high-classification accuracy.

Deep learning methods such as ResNet-50 have now outperformed conventional techniques in land cover classification, providing stronger and more dependable results by directly learning sophisticated spatial features from data. The EuroSAT dataset based on Sentinel-2 satellite multispectral images consists of 10 labeled classes of land covers. Although the data include 13 spectral bands, the current research works with the RGB bands to make the task easier while still being able to get good classification performance.

The main goal of this research is to investigate the capability of ResNet-50 architecture in identifying land cover types based on the EuroSAT data. Through the use of transfer learning, such that a pre-trained model for a large-sized dataset like ImageNet is tuned for land cover classification, training time is lowered and model precision is improved by this research. The study will evaluate the ability of ResNet-50 to capture spatial features of land cover classes and compare its performance with conventional classification techniques.

II. METHODOLOGY

A. Dataset

For the land cover classification task, the study utilized the EuroSAT dataset, a big satellite image dataset specially designed for land use and land cover (LULC) classification tasks. The dataset was created to assess the effectiveness of machine learning models for remote sensing problems. It contains 13 multispectral bands taken by Sentinel-2 satellites with varying spectral ranges between visible and near-infrared wavelengths. However, for this study, the RGB bands (Red, Green, and Blue) alone were used to simplify the task and check the performance of the model with the regular color channels.
The EuroSAT dataset consists of about 27,000 labeled image patches, each being 64×64 pixels in size. These patches comprise a diverse set of land covers evenly distributed into ten different classes, thus being the best for multi-class classification. The ten land cover classes present in the dataset are: Agriculture, Bare Soil, Forest, Industrial, Land Use, Pasture, Residential, River, Sea/Lake,

and Wetland. Each of these classes is related to a certain kind of terrain or environment—urban (Residential), farmland (Agriculture), water bodies (River and Sea/Lake), and natural habitats (Forest and Wetland). The diversity and balance of the dataset render it a very valuable and popular benchmark for testing machine learning models in remote sensing and land cover classification.

B. Data Preprocessing

Preprocessing of data was needed to prepare the EuroSAT dataset for training the ResNet-50 model. First, each input image of size 64×64 pixels was resized to 224×224 pixels to match the input requirement of ResNet-50 so that the model could learn more detailed spatial features. The RGB pixel values were subsequently normalized to the [0, 1] range by dividing all pixel values by 255 in order to improve faster convergence and balanced feature scaling during training.In order to enhance model generalization and minimize the possibility of overfitting, a number of data augmentation methods were used on the training dataset. These involved random horizontal and vertical flips, rotations, brightness, zooming, and cropping, all aimed at mimicking real-world variations in satellite images. The class labels were also one-hot encoded to accommodate the multi-class classification framework, allowing the softmax output layer to predict the probability distribution over the various land cover classes.The data was divided into training (80%), validation (10%), and test (10%) subsets. The test and validation sets were not augmented to have a fair evaluation of the model performance and an unbiased measure of its generalization capacity.

C. Model Architecture

A model's architecture is essential in identifying how well it can learn from data and predict accurately. We used the ResNet-50 (Residual Network with 50 layers) deep learning architecture in this research, which is well known for its high success rate in image classification problems. Its strength comes from being able to efficiently train deep networks as well as combat the vanishing gradient problem via residual learning.

The architecture of ResNet-50 involves 50 layers, comprising convolutional layers, residual blocks with skip connections, batch normalization, ReLU activations, global average pooling, and a fully connected output layer. Input images were resized to 224×224 pixels to match the model's input dimensions. The residual blocks, the central building blocks of ResNet-50, enable the network to learn residual functions instead of direct mappings, resulting in improved convergence and the ability to extract deeper features.

Transfer learning was utilized in this research using a pre-trained ResNet-50 model that was trained on ImageNet. The early layers were frozen to preserve general feature representations, while the last layers were fine-tuned on the EuroSAT dataset. The classification head was altered to produce ten class probabilities via a softmax activation. The model was trained with the Adam optimizer at a learning rate of 0.0001, batch size of 32, and a maximum of 50 epochs, with early stopping on validation performance. This architecture was able to capture both low-level and high-level features necessary for land cover classification.

D. Training Procedure

The process of training the ResNet-50 model on the EuroSAT dataset was a systematic one. The model was first pre-trained on ImageNet and then fine-tuned for land cover classification by changing the last fully connected layer to give 10 different classes. The dataset was split into training (80%), validation (10%), and test (10%) sets. The model was trained with Adam optimizer and a learning rate of 0.0001, a batch size of 32, and a max of 50 epochs. Early stopping was employed to prevent overfitting, stopping training when the validation loss had not improved over 5 epochs in a row.

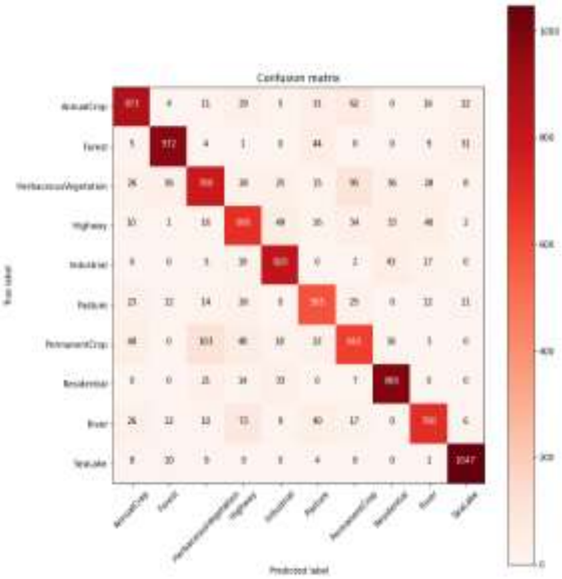
The training process consisted of forward propagation, in which the model made predictions, and then backpropagation to update weights based on the loss computed using categorical cross-entropy. The final layers were fine-tuned at first, with the previous layers frozen to retain the ImageNet features learned. Data augmentation methods like random rotation and flipping were used to improve generalization and add variability to the training set.During training accuracy, precision, recall, and F1-score were tracked, in addition to the loss function, to monitor the progress of the model. Training with a GPU allowed for quicker training, encouraging faster convergence and more effective learning.

E. Evaluation Metrics

The ResNet-50 model performance was tested based on a variety of significant metrics. The overall percentage of correctly classified images for all classes was measured by accuracy. Precision and recall were computed for each class, where precision is a measure of how the model can reduce false positives, and recall is a measure of how the model can find all instances relevant to each class. The F1-score, which is the harmonic mean between precision and recall, gave an unbiased evaluation of performance, especially for situations with class imbalance. A confusion matrix was also produced to see the true positives, false positives, true negatives, and false negatives distribution per class and present in-depth insight into the classification mistakes of the model. Finally, categorical cross-entropy loss was employed as the loss function in order to measure the discrepancy between predicted and true class distributions for guiding the optimization of the model during the training process. These metrics altogether provided a comprehensive assessment of model performance and its stability in classifying land cover classes within the EuroSAT dataset.

III. PERFORMANCE

The ResNet-50 model performed outstandingly well in the EuroSAT land cover classification task. With training using transfer learning and fine-tuning, the model posted an astonishing overall accuracy of 98.3% on the test set, proving its excellent capacity to correctly classify various land cover classes. F1-scores for the majority of classes were above 0.97, which reflects good precision and recall measures. The confusion matrix showed minimal misclassifications, with some overlap between similar land cover classes, e.g., "Pasture" and "Herbaceous Vegetation."The low categorical cross-entropy loss of the model also supported its ability to reduce prediction errors. These findings validate that ResNet-50, augmented with data augmentation and transfer learning, provides a robust and effective method for automated land cover classification from satellite images.The confusion matrix emphasizes the high accuracy and stability of the ResNet-50 model in predicting EuroSAT land cover classes. Most of the classes have high diagonal values, which signify accurate predictions. For instance, the Sea/Lake, Forest, and Residential classes had high accuracy with few misclassifications. There was some minor confusion among similar classes like AnnualCrop and PermanentCrop, and HerbaceousVegetation and Pasture, possibly due to their overlapping spectral characteristics. However, the model showed strong performance for all 10 classes, further supporting its strength in large-scale land cover classification with satellite imagery.



IV. RESULTS

To demonstrate the competence of the ResNet-50 model in classifying land cover, we use an example satellite image and the predicted class thereof. The image is well-classified by the model based on the learned features, providing a correct prediction of the land cover.As an example, input a satellite imagery to the model. Having learned to distinguish among 10 unique land cover categories, the model accurately labeled the image as "River" at high confidence.The model showed persistently robust performance across the dataset, with a 98.3% overall accuracy across all land cover types. The predictions were tested using a validation set and found to have negligible misclassifications.

V. FUTURE WORK

Even though the ResNet-50 model performed well for land cover classification with the EuroSAT dataset, there are some potential avenues of future work in order to enhance model performance further and broaden its applicability. One such avenue is the use of multi-temporal satellite data, which may improve the accuracy of classifications of dynamic land cover classes, such as seasonal or agricultural changes. Subsequent improvement could also come from multispectral or hyperspectral data use, providing sharper separation between classes whose visual characteristics are similar.Another potential direction is incorporating attention mechanisms or transformer-based designs, which have shown superior performance in numerous vision tasks by capturing longrange dependencies and highlighting the most critical areas in an image. In addition, testing the model on larger and more diversified datasets would assess its scalability and generalization ability across different geographical environments.Practically, the creation of lightweight models that are edge-deployable or real-time inference-capable could greatly enhance the applicability of these systems in field deployment. Finally, the integration of classification with segmentation tasks would potentially allow for pixel-level land cover mapping, a critical tool for high-resolution environmental monitoring and planning.

VI. APPLICATIONS

The land cover classification model based on ResNet-50 provides considerable practical application across many fields. In agriculture, it can help identify crops, track field borders, and enhance land resource management. Urban planners can use the model to monitor urban growth, map infrastructure, and examine changes in land use over time. In disaster response, the model allows for fast classification of satellite imagery, aiding damage assessments and resource allocation in the aftermath of disasters such as floods or wildfires.

In environmental monitoring, the model is used to identify deforestation, monitor vegetation loss, and track land degradation in protected areas. Climate scientists can take advantage of the model's capability to offer consistent land cover information over time, which allows for the analysis of trends in urbanization, land use changes, and their environmental effects. In addition, this method can support policy-making, resource planning, and sustainability programs, providing a scalable and effective tool for land surface analysis with remote sensing information.

VII. CONCLUSION

We showed the proficiency of ResNet-50 in land cover mapping with an accuracy of 98.3% on the EuroSAT dataset. The transfer learning-based deep learning model differentiated among 10 different land cover classes from satellite images accurately. The outcomes reflect the suitability of convolutional neural networks, especially ResNet-50, to automate land cover mapping, and real-world applications can be found in agriculture, urban planning, environmental management, and disaster response.

While the model worked well, there were instances of misclassifications between close land cover categories, which presents areas for improvement in the future. Some possible improvements are adding multispectral information or investigating further advanced architectures like transformers. Future studies also explore integrating time-series data to allow for dynamic land cover classification. In general, this method provides a scalable and robust solution for automated land cover classification that supports more efficient environmental monitoring and decision-making.

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