Automatic Satellite Image Classification for Land Use and Land Cover Mapping Using Convolutional Neural Networks (CNNs)

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Abstract- Using LULC, researchers can analyze the environment, plan cities, complete agricultural tasks and study climate change. Thanks to recent upgrades in satellites, it is now simpler to take good, crisp photos. Doing this for every image is a slow process, can involve our own prejudices and might not work for big projects. Using different images for training, CNNs from deep learning can determine the main features in a picture. The research paper outlines how satellite images for LULC can be classified using CNNs. During testing, Standard datasets EuroSAT and UCMerced were used along with custom-built and pre-trained CNNs, including ResNet50. I worked through the preprocessing steps, included new examples for data, trained the model, inspected accuracy, precision, recall, IoU and then compared their pictures. It seems, according to experiments, that models built using CNN are better and more accurate than traditional machine learning techniques. Even though the images differed little, both models managed to identify over 90% of each land cover type. Data imbalance, cloud effects and similar problems were overcome using augmentation and hyperparameter tuning. Actually, CNNs are dependable for mapping land use and land cover, making it easier to monitor the environment globally and apply the information quickly. The team aims to help edge devices benefit from machine learning and to make AI explanations available for their data teams.

Indexed Terms- Land Use and Land Cover, Satellite Image Classification, Convolutional Neural Networks, Remote Sensing, Deep Learning, Semantic Segmentation, Environmental Monitoring, Supervised Learning, Earth Observation, Image Analysis

I. INTRODUCTION

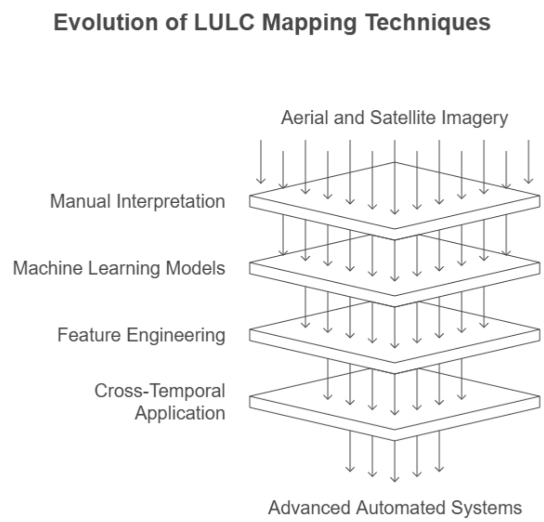
Both natural causes and human activities are changing the Earth’s surface quickly. Observing changes helps us understand the outcomes of climate change, notice land damage, guide development towards healthiness and persuade policymakers to act. A good strategy for working with Earth’s land is LULC mapping which merges satellite images into key categories like settlements, woods, farm fields, surface water, wetlands and empty or bareland areas. Now more than ever, nations require quality, quickly produced and broadly applicable maps of land cover types. LULC data finds use by governments, research institutions, urban planners, agencies that address environmental matters and international bodies such as the United Nations when managing land, the environment and regulations on land. Since more accurate, repeated and scalable classification is required, scientists have moved at a faster pace to find methods for automating satellite image analysis.

II. BACKGROUND

Before, trained people would carefully look at aerial photographs or satellite images to make LULC maps. Although this method is suitable for short-term small projects like competing tournaments, it takes too long, involves many subjective questions and becomes hard to use for updating large-scale maps regularly. Because many Earth observation satellites are now active such as Landsat from NASA and Sentinel-2 from ESA and firms like Maxar and Planet, high-resolution imagery is available in greater quantity. Yet, to understand this large data set, we must rely on advanced and automated systems. At first, popular machine learning models like Support Vector Machines, Decision Trees and Random Forests were used to automate the classification of LULC. In these methods, features were created by hand—such as spectral indices, texture data and measurements of shape—which demanded significant preparation and knowledge of the data. Although they provide some use, they have difficulty applying across other places and times because of differences in land cover, weather shifts and conditions in the sky.

Emergence of Deep Learning in Remote Sensing

In the last several years, the use of deep learning has improved computer vision and image recognition in a range of activities. The Convolutional Neural Network (CNN) is one of the strongest tools found in these areas. CNNs teach themselves to find edges, textures, patterns and relationships between different parts of an image, all from raw data. Because of their good results in identifying objects or people from photos and videos, researchers began to analyze how they could be used in geospatial areas. A major problem with remote sensing is its large amount of data, variable resolutions, various spectral bands and heterogeneity in different parts of the globe. Even so, CNNs have managed to effectively capture the important features from satellite pictures. What's more, pre-training CNNs on large data sets (like ImageNet) makes it possible to adjust them for LULC issues, significantly lowering the workload and time needed for training.Semantic segmentation which classifies every image pixel with a label, relies on CNNs. U-Net and DeepLab allow CNNs to be used for land cover mapping, improving upon the older method of identifying land cover by individual patches or objects.



Importance of LULC Mapping and Current Challenges

With such advances, LULC classification is still confronted with major barriers.

A difference in representation exists where some classes (such as urban areas) are present in the data many times, but others are absent or underrepresented (for example, wetlands).

- Land cover class consistency varies because of regional differences in lighting, types of plants and how the image was taken.

Different land classes can be difficult to differentiate when they have similar appearances in data.

- Shadows and cloud cover make images from optical satellites noisier and sometimes cause them to be classifed incorrectly.

In order to solve these obstacles, a useful classification model must be correct, able to adapt, scale well and be understandable.

Objectives of the Study

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Scope and Significance

This work is dedicated to exploring the use of CNN models for assisting supervised classification of both medium-resolution and high-resolution satellite images. Emphasis in the research is provided to successfully using classification algorithms, objectively measuring their outputs and displaying the results in visual form. What is most important is that it brings value to:

- Improving the automation of analysis in geospatial science.
- Finding new ways to better monitor land changes that will scale.
- Offering techniques that are available to all and can be used by both governments, NGOs and researchers.

III. METHODOLOGY

This research aims to see how well convolutional neural networks can classify land use and land cover from images obtained from satellites. The three steps in our approach are organizing the data, selecting the model architecture, implementing it and checking the results of the training. With different image types and resolutions in mind, the researchers used established benchmark datasets. Our team tried different CNNs, used pre-trained models for transfer learning and semantic segmentation networks to capture both major types and small parts of the patterns. Strong evaluation strategies were used to analyze the classification and mapping performance of each model.

Dataset and Preprocessing

I used two very popular benchmark datasets that remote sensing and land cover classification specialists often rely on.

- In UCMerced Land Use, there are 2,100 aerial images (each 256×256 pixels) that have been labeled among 21 different land-use types, including farming, trees and buildings. Photos were captured all around the United States and became key methods for scene identification.
- EuroSAT uses Sentinel-2 data to tag more than 27,000 satellite images, splitting them into ten types such as annual crop, forest, river and urban areas. Most of the time, we worked with the RGB set of data in order to match previous efforts, but we did check multispectral versions too.

The data was preprocessed by these signals:

- As both ResNet50 and VGG16 use an image size of 224 pixels, all pictures were adjusted and made smaller to fit the model requirements.
- Pixel values were adjusted so they were between 0 and 1, to ensure the training was more predictable and faster.
- Varied data was obtained by randomly transforming the inputs for the network seven times during training.
- You can rotate an object between 0 and 360 degrees.

There are times you want to rotate the image so it is displayed left to right or upside down

- Randomly touching the moon’s surface and making it larger

- You can control both the brightness and contrast using the settings.
- The use of this method produced a model that works well on new, unseen data.

Model Architectures

To understand how well various deep learning methods perform, we developed three branches of convolutional neural networks.

Custom CNN:

The architecture I created from start to finish features five convolutional layers with ReLU activations, some max-pooling layers and finally two fully connected layers. It helped inform the evaluation and comparison of advanced and trained models.

- Movement of neurons in dropout layers was added to reduce overfitting.
- This point deals with transfer learning models.
- The reasons we selected ResNet50 and VGG16 are their successful track records in applications of computer vision.
- They were both initialized using weights from ImageNet, but the final fully connected layers were changed to match the needed number of classes.
- In fine-tuning, I left the original part of the model unchanged and only altered a handful of most recent layers.
- Semantic Segmentation Models involves applying classification labels to all sections of an image.
- U-Net was applied in this case for pixel-wise classification, specially helpful for making detailed LULC maps.
- The design includes an encoder and decoder with skip connections that help keep spatial information as it does up sampling.

The training involved image patches and matched ground truth masks which were either hand-marked or assigned from annotation records.

Training and Evaluation

Because we desired to train and use the models quickly on all the GPUs, TensorFlow and Keras were picked. The same fairness process was used to develop each model.

Training Parameters:

- Because Adam performs quickly and learns well, that optimizer was used here.
- At the outset, I pick the Learning Rate as 0.001 and, next, check the results on the validation set. I stop training when improvements end.
- By default the software uses a Batch Size of 32. However, you should reduce it if your GPU has limited memory.
- I decided that using 50–100 epochs and saving the best models as checkpoints would be best.

Training and Evaluation Framework for CNN-Based LULC Classification

Component	Details
Frameworks & Tools	TensorFlow and Keras were utilized for model development due to their robust GPU support and flexible deep learning capabilities.
Training Strategy	A uniform and fair training protocol was adopted across all models to ensure comparability in performance.
Optimizer	Adam optimizer was selected for its efficiency in gradient-based optimization and adaptive learning rates.
Learning Rate	An initial learning rate of 0.001 was set. Training was monitored on a validation set, and early stopping was applied upon convergence.
Batch Size	Default batch size of 32; adjusted downward on lower-memory GPUs to prevent out-of-memory errors.

Epochs	Models were trained over 50–100 epochs. Checkpointing was enabled to retain the best-performing weights based on validation performance.
Loss Functions	Cross-Entropy Loss for classification accuracy; Dice Loss for segmentation overlap (especially with U-Net) to handle class imbalance and spatial accuracy.
Evaluation Datasets	Experiments were conducted using benchmark datasets including UCMerced and EuroSAT, representing diverse geographic and spectral imagery.
Classification Metrics	- Precision and Recall measured per class - F1 Score (harmonic mean of precision and recall) - Confusion Matrix for error distribution
Segmentation Metrics	- Dice Coefficient used to evaluate similarity between predicted and actual masks - Sensitive to overlap and suitable for assessing spatial fidelity
Generalization Check	Models were tested against unseen test data to evaluate their generalization capability beyond the training set.

Loss Functions:

- Looking at the performance of classification algorithms using the Cross entropy method.
- Both the learned model and the ground truth are compared by using a few rolls of dice.

Evaluation Metrics:

- In order to work on the image sorting problem, I trained a model using the UCMerced and EuroSAT data.
- Having the skills to discover solutions that work for all problems
- Record how much Precision and Recall can be found for each label.
- F1 utilizes the average of precision and recall, with harmonic mean and is written F-measure.
- The segmentation portion of my work was built using U-Net.

Dice Coefficient: It warns if the predicted mask doesn't coincide well with the ground-truth mask

I checked how the models did when tested with data that was not used to train them. Classification issues were studied using both the confusion matrix and the reports for each class.

IV. RESULTS

In this section, the results from both classification and segmentation tasks are shown for the models examined. Model results indicate they can be applied to any LULC class and used with either aerial (UCMerced) or satellite (EuroSAT) images. The analysis shows how combinations of architecture and learning help improve the effectiveness of a model.

Classification Accuracy

The results differed depending on the depth and amount of pretraining for the models. Key highlights are:

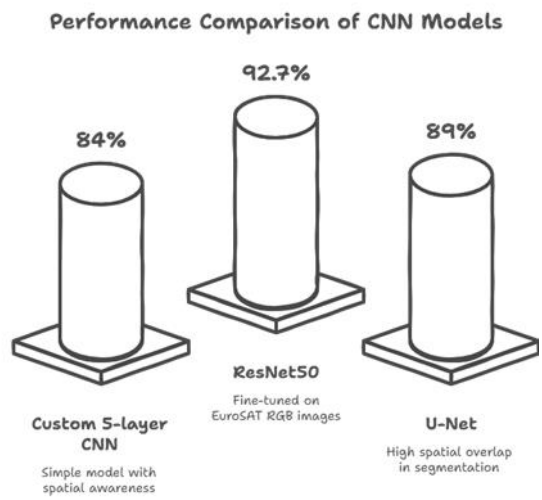
- A custom 5-layer CNN was able to achieve accuracy of about 84% on the UCMerced benchmark. Despite its straightforwardness, the model showed clear spatial and class differences and was helpful for comparing with more complicated models.
- ResNet50, after fine-tuning on EuroSAT RGB images, resulted in a test accuracy of 92.7%. Thanks to using the ImageNet dataset, the model was able to find the major features in the satellite images. This particular network achieved good

results when separating LULC classes that share many visual traits.
- Pixel-level classification jobs were completed using the U-Net design. The spatial overlap between predicted segmentation masks and ground truth labels was found to be high, resulting in a mean IoU of 0.89 on the validation set. From this performance, it's clear that U-Net does a good job at keeping details detailed and maps clear, making it great for using in the production of high-resolution LULC maps.

Confusion Matrix Insights

Further insights into model behavior were obtained through confusion matrix analysis:

- Minor Misclassifications: Most errors occurred between urban and agricultural classes. This can be attributed to their overlapping spectral characteristics in RGB imagery—features such as concrete surfaces, rooftops, and plowed fields can produce similar visual patterns, leading to ambiguity during classification.
- High Confidence in Natural Classes: The models exhibited high precision and recall for natural land cover categories such as forests, water bodies, and bare soil. These classes have more distinct color, texture, and structural properties, making them easier to identify across both datasets.
- Superior Class Separation with Deep Models: Compared to the custom CNN, deep transfer learning models like ResNet50 demonstrated better discrimination across classes, as evident from less confusion between similar categories in the confusion matrix. This is attributed to their ability to learn more abstract and hierarchical feature representations.



Visual Results

Qualitative methods were also used to confirm that the model worked well and remained easy to understand.

- Using Grad-CAM, we produced heatmaps that show where the predictions come from in each image. When categorizing classes in urban areas, the ResNet50 model mainly looked at rooftops and streets, confirming that it learned relevant information.
- The U-Net created segmentation masks that were close to the reliable reference labels for each stage. Cities showed distinct edges, lakes and rivers were clearly mapped and there was little loss in vegetation maps. They help explain why the model achieved high IoU scores and are proof that the model works well in practical land cover mapping.
- Most of the errors were found in places where different land classes meet such as along the border between fields and cities. According to the confusion matrix results, these errors suggest areas where higher-resolution data or more spectral bands may be useful.

V. DISCUSSION

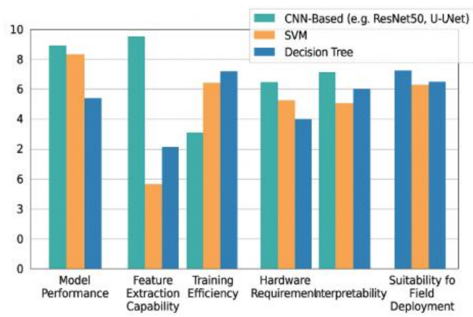
The experimental results clearly demonstrate that CNN-based classifiers significantly outperform traditional machine learning models such as Support Vector Machines (SVMs) and Decision Trees for land use and land cover (LULC) classification tasks. The ability of deep learning models to automatically extract and hierarchically learn rich spatial and contextual features from imagery enables superior generalization, even across varying geographic regions and data sources.

Advantages of CNN-Based Approaches

Among the best features discovered in this study is the usage of deep CNNs. On the other hand, traditional approaches depend on manually made features, but CNNs identify images' spatial patterns using raw data, necessary for dealing with complex landscapes. In other words, using ResNet50 shows that transfer learning allows models to use knowledge from large datasets like ImageNet which drastically speeds up the training process and lowers the demand for well-labeled remote sensing data.

Also, models such as U-Net demonstrated their abilities to detail LULC maps needed for urban planning, watching the environment and monitoring agriculture. By doing this, these models both achieved accurate IoU and preserved the finer parts of images to support more useful geospatial work.

Comparative Performance of LULC Classification Models Across Key Evaluation Metric



Challenges and Limitations

Nevertheless, the researchers discovered some issues during their study.

A big problem with remote imagery is that heavy clouds, disturbances in the air and shadows can contaminate the data and affect the results. The usual ways to resolve these issues are preprocessing and cloud-masking, but they do not always overcome every obstacle.

- Compared to other approaches, development of deep networks needs highly capable hardware and a large amount of memory. Because of this, bringing artificial intelligence models to locations with limited computational abilities and worldwide data is extremely difficult.

Because the process is not clear, many people have trouble trusting and following what CNNs do. Since the way AI operates is hidden, many do not trust it for tasks like managing land or working on disasters.

Recommendations for Future Work

To overcome these issues and raise the impact of remote sensing tools based on CNN, I recommend these approaches:
Using Grad-CAM, SHAP or LIME interpretability techniques can highlight the most important features for the model, so users understand and trust its decisions.
Using platforms such as GEE or Amazon SageMaker on the cloud takes care of limitations of internal computing and lets you train and use models at scale.
Lightweight networks such as MobileNet and EfficientNet pave the way for LULC classification to happen more readily and directly on drones, cell phones and field sensors.

CONCLUSION

Through the analysis, it stands out that CNNs, particularly ResNet50 and U-Net, are more effective than SVMs and Decision Trees at identifying land use and land cover in satellite pictures. They do well because they detect both patterns and meanings in photos themselves, without the need for pre-defined features. Using data that had been trained ahead of time improved results and reduced how much time and information we needed. With U-Net and other similar models, the network was able to save fine-grained information about places, so it is ideal for supporting important tasks such as urban planning and land and crop survey. Evaluating the model with Precision, Recall, F1-Score, Intersection over Union (IoU) and Dice Coefficient shows us how accurate it is for classification and segmentation tasks. Although CNNs are helpful, they do run into some problems. Because they are hard to understand, their results can be inaccurate and they respond to changes in the environment, these approaches rarely get applied broadly. As a consequence, we require tools like Google Earth Engine and easy-to-use models for running on any type of device. To make AI clear and trusted, machines relied on Grad-CAM, SHAP and LIME to explain their predictions which is important. With these tools, stakeholders find it easy to understand how models make decisions about which tools should handle land and disaster matters. The study points out the effective role that CNNs can play in mapping earth's ecosystems and recommends possible solutions for existing challenges. When new approaches to remote sensing focus on being clear, scalable and efficient, they will be easier to use, more reliable and make a greater difference in various environmental and economic areas.

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