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A BENCHMARK COMPARISON OF SIMPLE CNN, RESNET-50, AND EFFICIENTNET FOR IMAGE CLASSIFICATION

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SUMMARY

Terrain Type Identification is an essential aspect of environmental monitoring, urban planning, and resource management. This study discusses a comparative investigation of the effectiveness of three Convolutional Neural Network (CNN) architectures Simple CNN, ResNet-50, and the Enhanced Efficient CNN Model which is Efficient Net in training with the Euro SAT dataset of 27,000 geo-referenced Sentinel-2 satellite images in 10 land cover classes. This paper also examines the role of preprocessing techniques including image resizing, data augmentation, and normalization in improving the overall performance of the models. The effectiveness of each model was closely observed by looking at how they recognized different land cover types, ensuring balanced performance across all classes. Experimental results indicate that the Efficient Net model has the highest classification accuracy of 97.5%, followed by Simple CNN with the accuracy of 94% and ResNet-50 with the accuracy of 89%. Furthermore, simple scaling preserves RGB features better than grayscale conversion. The study's results emphasize the need for selecting suitable model structures and preprocessing methods for successful terrain type identification through the use of remote sensing imagery, which concludes with the creation of efficient deep learning models for remote sensing.

Key words: *land cover classification, eurosat, cnn, efficientnet, resnet-50.*

INTRODUCTION

Terrain Type Identification has to be accurately classified in order to support a vast range of modern applications, from improving their use in agriculture and disaster avoidance to urban planning and environmental surveillance [1], [2], [19]. As the activity of humans continues to exert pressure on natural ecosystems, there's an urgent need for intelligent systems that can automatically analyze large volumes of satellite imagery and classify land surfaces with high accuracy as well as precision. Sentinel-2 and the ESA-operated satellite offers high quality multi spectral images that are particularly valuable in analyzing the type land area, because of their model's ability to effectively capture high spatial and spectral resolutions from the satellite images [3]. These satellite images are, however, usually intricate and heterogeneous and therefore pose the difficulty of maintaining uniform classification accuracy over various regions and environmental contexts [23].

Conventionally, Terrain Type Identification has been based on hand-designed features and traditional machine learning algorithms like Decision Trees, Support Vector Machines (SVMs), and Random Forests [4], [5]. These models have been demonstrated in certain applications but are prone to being extremely sensitive to noise and demanding a high level of domain knowledge for feature engineering and parameter setting. Furthermore, their performance is suboptimal when used with multi-spectral satellite images that come in different resolutions and textures [6], [22].

The solution of this image classification challenges has changed with the introduction of deep learning, specifically Convolutional Neural Networks (CNNs) [7],[8]. CNNs are ideal for the satellite image interpretation and remote sensing because they can automatically learn complex spatial hierarchies and structures from raw image data [20].

This study compares and analyzes the performance of the three major CNN architectures for Terrain Type Identification: Simple CNN, ResNet-50, and EfficientNet. Over 27,000 satellite photos classified into ten different land cover classes are included in the dataset provided from the EuroSAT [9]. Furthermore, the study determines how various image preprocessing methods such as data augmentation, image resizing and normalization affect the performance of the model [10], [13]. Multiple optimization techniques were also used for determining the best optimization technique. The study also finds the best model architecture and preprocessing technique for satellite image classification by carrying out regulated tests with constant training settings and data handling techniques. Finding the best deep learning model for classifying satellite images is the objective of this study [11].

In conclusion, this study finds the best suited deep learning system for Terrain Type Identification. The study also compares the various models such as the Simple CNN, ResNet-50 and EfficientNet model along with preprocessing methods like image resizing and data augmentation to pick out the best model. Standard performance criteria such as the accuracy, precision, F1-score and recall are used in the evaluation process to provide a thorough evaluation of the usefulness for practical geographic applications.

RELATED WORKS

Terrain Type Identification using satellite images has undergone a significant change in methodology over the passing years, straying away from traditional machine learning techniques and towards newer deep learning models. This is mostly because of the existence of deep learning techniques that are able to recognize intricate spectral and spatial patterns in extremely complex datasets far more accurately as well as precisely. Previous works in this area often used models like Support Vector Machines (SVM) and Random Forests (RF), which relied on manually selected features and had trouble with keeping up with the size and complexity of multi-spectral satellite data [21], [12]. The introduction of Convolutional Neural Networks (CNNs) has shown to be a massive step up in remote sensing applications. Among the many architectures developed, ResNet 50 stood out for its innovative residual learning framework, which significantly improved classification accuracy across multiple domains, including satellite imagery analysis [24]. On the other hand, simpler CNN models, while more limited in depth, offer benefits in terms of computational efficiency and continue to be useful as baseline models in Terrain

Type Identification studies [14]. EfficientNet introduced a smart method of scaling, modifying the depth, width, and resolution of the network in a balanced manner. This not only improved accuracy but also maintained computational resources within bounds, making it both strong and efficient. [15].

Sentinel-2 satellite images was used to create EuroSAT, one of the most widely used databases in this field. The dataset contains information in 13 spectral bands and more than 27,000 tagged photos that represent 10 different land cover types. For the assessment and testing of deep learning models in Terrain Type Identification classification tasks, this makes it an ideal benchmark [16]. Preprocessing techniques like data augmentation and patch based image splitting have been found to be effective in improving model generalization in previous studies employing CNN architectures on EuroSAT, with encouraging results [17]. Though they haven't been fully applied to the identification of terrain types based on EuroSAT data, techniques like histogram equalization and CLAHE have found use in the majority of image processing operations. They are therefore a very intriguing choice to investigate in subsequent studies [18].

Based on this, the current research compares three deep learning architectures: Simple CNN, ResNet-50, and EfficientNet. Their performance on the EuroSAT dataset is compared to analyze their performance. Standardized preprocessing methods such as data augmentation and image patching are used to train each model. The final aim is to classify the provided images under the 10 disparate classes based on their characteristics and applications in the best possible manner

STUDY AREA

The research relies on the EuroSAT dataset of 27,000 georeferenced images obtained from the European Space Agency (ESA) Sentinel-2 satellite. The images correspond to 10 different land use and land cover classes, such as agricultural lands, forests, residential, rivers, and highways, among others. Each image is of dimension 64×64 pixels and uses 13 spectral bands (from visible to infrared), which enable complete spectral and spatial analysis of the Earth's surface.

The dataset covers diverse geographic regions across Europe, providing a representative sample of real-world terrain and land use contexts. Its diverse topography and homogeneous data structure make it an appropriate benchmark to train and test deep learning models for remote sensing applications. Employing this large dataset, the work seeks to evaluate the generalizability and performance of different CNN architectures under homogeneous environmental and spectral conditions.

PROPOSED SYSTEM

We have created a deep learning model to categorize different types of terrain from Sentinel-2 satellite high-resolution multispectral images. EfficientNet—a new CNN which is highly accurate and efficient—lies at the core of everything. It is an excellent candidate for this kind of task as it is both very accurate and efficient. The model is trained to categorize satellite images into ten specific EuroSAT dataset-defined land cover classes as shown Figure 1. Our pipeline covers the entire cycle from image capture to deployment, including important steps like preprocessing, model architecture, training, and real-time inference.

Data Collection & Preprocessing

Satellite imagery from the Sentinel-2 missions, which capture data in 13 different spectral band ranging from visible light to near-infrared. This gives us a highly detailed and rich observation of the Earth's surface. To make this raw data usable for training, the following preprocessing operations are performed:

1. **Geo-referencing:** Converts image pixels to geographic coordinates using latitude and longitude.
2. **Band Selection:** Focuses on the most informative bands – B2 (Blue), B3 (Green), B4 (Red), and B8 (NIR).
3. Resizing: Images are resized to 224×224 pixels to meet the input size the CNN anticipates.

4. **Normalization:** Pixel values are normalized to the range [0, 1] to ensure uniformity while training.

5. Data Augmentation: Flipping, rotation, scaling, and cropping are used to artificially augment the dataset and enhance the model's robustness.

After preprocessing, we now have a clean data of 27,000 pre labeled image tiles allocated to one of ten land cover categories, like residential, industrial, or forest.

Model Architecture

We use the EfficientNet model, which introduces a compound scaling method that balances three critical dimensions of CNNs—depth, width, and resolution—through a single scaling factor (φ). The scaling relationships are defined in (1).

$$md = \alpha^{\varphi}, \quad w = \beta^{\varphi}, \quad re = \gamma^{\varphi}, \quad \text{with the constraint: } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \tag{1}$$

This approach ensures balanced and computationally efficient scaling.

EfficientNet leverages MBConv (Mobile Inverted Bottleneck Convolution) blocks with residual connections that help preserve important features and avoid vanishing gradients. Each MBConv block performs a transformation as defined in (2).

$$F_{i+1} = F_i + MBConv_i(F_i) \tag{2}$$

At its core, the model applies standard convolution operations as defined in (3):

$$z = (t * k) + b \tag{3}$$

Where:

- t = input tensor,
- k = kernel,
- b = bias,
- $*$ = convolution operator.

The output is then passed through a

ReLU activation function for non-linearity:

$$f(t) = \max(0, t)$$

Output Layer: Classification

The final output layer generates a 10-dimensional probability vector, with each value representing the likelihood of the image belonging to one of the ten land cover categories. This is achieved using the softmax function as defined in (4):

$$\hat{y}_i = e^{z_i} / \sum_{j=1}^{K} e^{z_j} \tag{4}$$

Where:

- $\hat{y}_i$ is the predicted probability for class i,

- z_i is the raw logit score from the final dense layer,
- K is the number of classes (10 in this case).

The class with the highest probability is selected as the predicted label.

Training Strategy

We train the model using categorical cross-entropy loss—it's a go-to choice for multi-class classification and helps the model learn to tell the difference between multiple terrain types effectively as defined in (5):

$$\mathcal{L} = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \cdot \log(\hat{y}_{ij}) \qquad (5)$$

Where:

- N = number of samples,
- K = number of classes,
- y_{ij} = 1 if sample i belongs to class j, otherwise 0,
- $\hat{y}_{ij}$ = predicted probability for class j of sample i.

The Adam optimizer dynamically adjusts learning rates during training. To prevent overfitting, we apply early stopping, halting training when the validation performance no longer improves.

We evaluate the model using classification accuracy:

$$\text{Accuracy} = (\text{Correct Predictions}/\text{Total Predictions}) \times 100$$

The model achieves an impressive 98.57% validation accuracy, reflecting strong generalization.

Prediction & Real-Time Inference

After training, the model can classify new, unseen satellite images. These images go through the same preprocessing steps before being passed to the trained EfficientNet model, which outputs the predicted land cover class along with a confidence score—enabling fast, automated Terrian Type Identification classification in real time.

Applications and Objectives

This system has real-world applications across multiple domains, including:

1. Tracking the condition of the land as it changes over time.
2. Enhancing GIS map updates with accurate classification data.
3. Supporting urban development, environmental planning, and disaster response.
4. Assisting agriculture through large-scale vegetation monitoring and crop analysis.

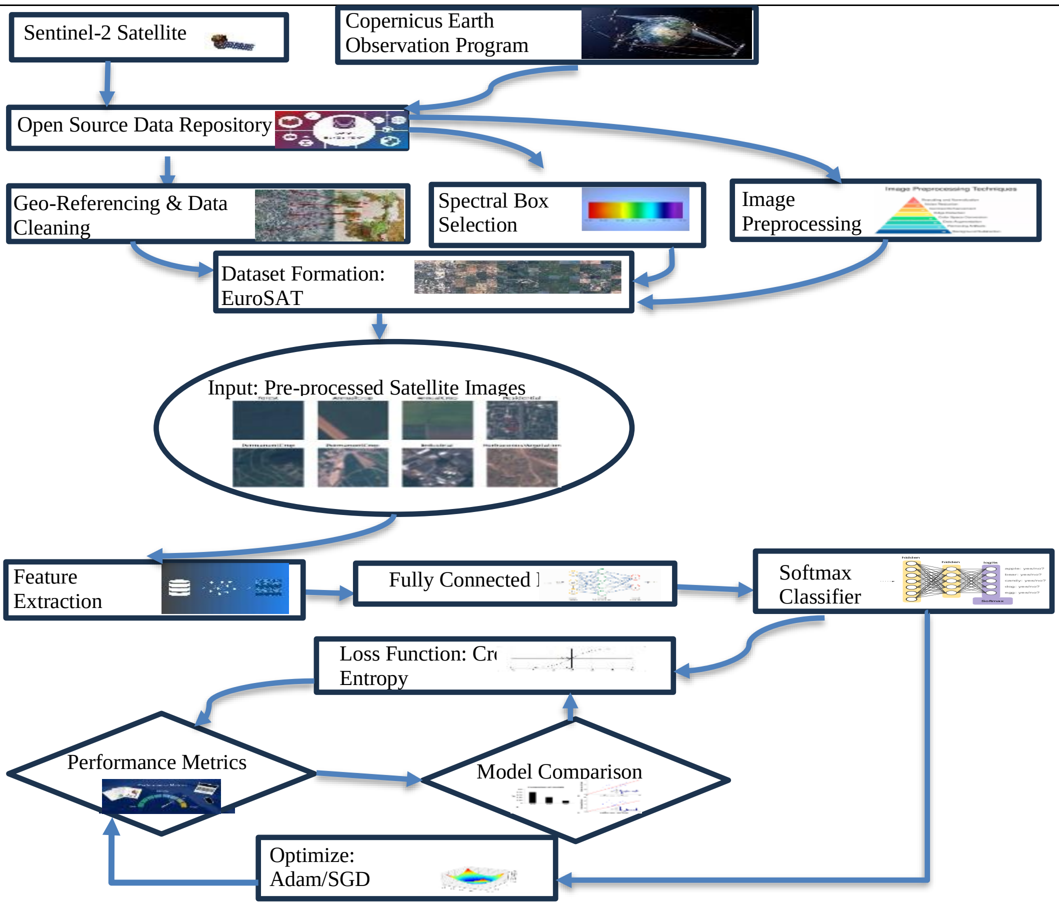


Figure 1: Architecture for the ten land cover classes

Algorithm 1. Terrain Type Identification using EfficientNet-B0

Input:

I → Set of Sentinel-2 multispectral images

C → Set of class labels (EuroSAT, 10 classes)

φ → Compound scaling coefficient

α, β, γ → Scaling hyperparameters

η → Learning rate

E → Number of training epoch

1: Initialize EfficientNet-B0 architecture with input size 224 × 224

2: for each image $I_i \in I$ do

3: Perform geo-referencing of I_i using spatial metadata

4: Select relevant bands: {B2, B3, B4, B8}

5: Resize I_i to 224×224 pixels

6: Normalize pixel values to range [0,1]

7: Apply data augmentation to I_i

8: end for

9: Modify final fully connected layer for $|C| = 10$ output classes

10: Scale network width w, depth d, and resolution r using:

$d = \alpha^{\varphi}, \quad w = \beta^{\varphi}, \quad r = \gamma^{\varphi}$

subject to: $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$

11: for epoch = 1 to E do

12: for each batch $B \in I$ do

13: Extract features F_i via MBConv blocks with residuals:

$F_{i+1} = F_i + MBConv_i(F_i)$

14: Apply convolution: $z = (x * w) + b$

15: Activate using ReLU: $f(x) = \max(0, x)$

16: Output logits z_j for each class j

17: Apply Softmax: $\hat{y}_j = e^{z_j} / \sum_{k=1}^{K} e^{z_k}$

18: Compute categorical cross-entropy loss:

$$L = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \cdot \log(\hat{y}_{ij})$$

19: Update parameters using Adam optimizer:

$$\theta \leftarrow \theta - \eta \nabla L$$

20: end for

21: Evaluate validation accuracy

22: Apply early stopping if validation performance plateaus

23: end for

24: for each test image I_t do

25: Apply same preprocessing pipeline

26: Predict class using trained model

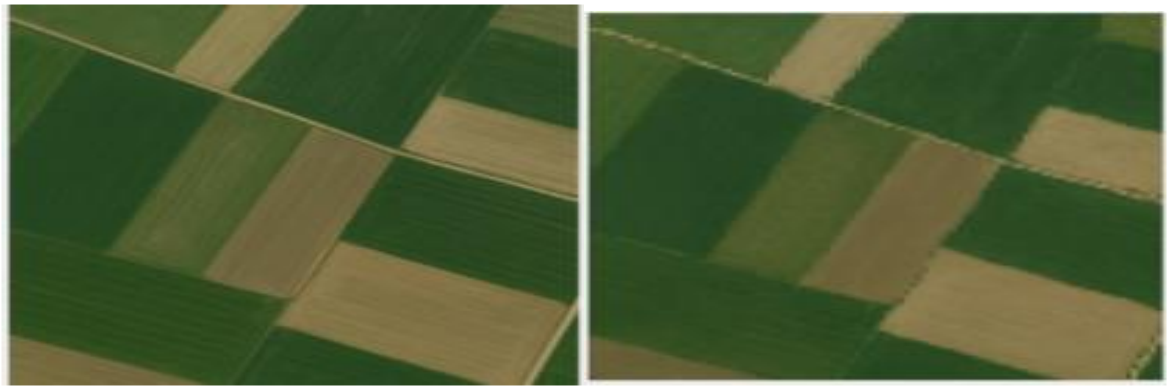
27: Assign class with highest $\hat{y}_j$ as final prediction

28: end for

Output: Predicted land cover class for each image

RESULT AND DISCUSSION

A visual comparison of satellite images before and after preprocessing as shown in Figure 2: On the left, the original image retains rich texture and detail, with fine boundary lines between agricultural plots. The image on the right, post-preprocessing, appears smoother and more uniform. This transformation, although it may lead to a minor loss in texture, significantly enhances the model's ability to extract essential features by removing noise and irrelevant high-frequency details. Such preprocessing steps were essential in improving model input consistency, especially given the variability inherent in satellite data.



Before Preprocessing After Preprocessing

Figure 2: The comparison between the image before and after preprocessing

The classification process begins with the retrieval of satellite imagery from the EuroSAT dataset, which includes 27,000 geo-referenced images sourced from Sentinel-2 as shown in Figure 3. Each image is labeled according to one of ten specific land cover categories, such as agricultural fields, forests, roads, residential areas, and water bodies. These images, initially captured across 13 spectral bands, are first subjected to preprocessing operations like band selection, normalization, and resizing to prepare them for model training. Once preprocessed, the images are fed into deep learning models that categorize each image into its respective land cover class by learning spatial and spectral patterns. This task is approached as a supervised multi-class classification problem, with each input image associated with a single, known label. The objective is to enable the model to distinguish between diverse landscape types based on image features, thereby supporting accurate and automated land cover classification in remote sensing applications.

Annual Crop

Industrial

Sea Lake

Pasture

Forest

Permanent Crop

Herbaceous Vegetation

Residential

Highway

River

Figure 3: Classification of different class of images

The progression of training and validation accuracy over 20 epochs is illustrated in the Figure 4. As observed, the training accuracy remains relatively consistent, fluctuating slightly around the 11% mark. However, the validation accuracy displays significant volatility, with occasional abrupt spikes in early and mid-epochs. These inconsistencies in validation accuracy may indicate that the model is struggling to generalize across unseen data, possibly due to factors such as class imbalance or insufficient training iterations. Despite this, the training accuracy shows mild improvement towards the later epochs, suggesting the model is learning gradually but lacks robustness in generalisation.

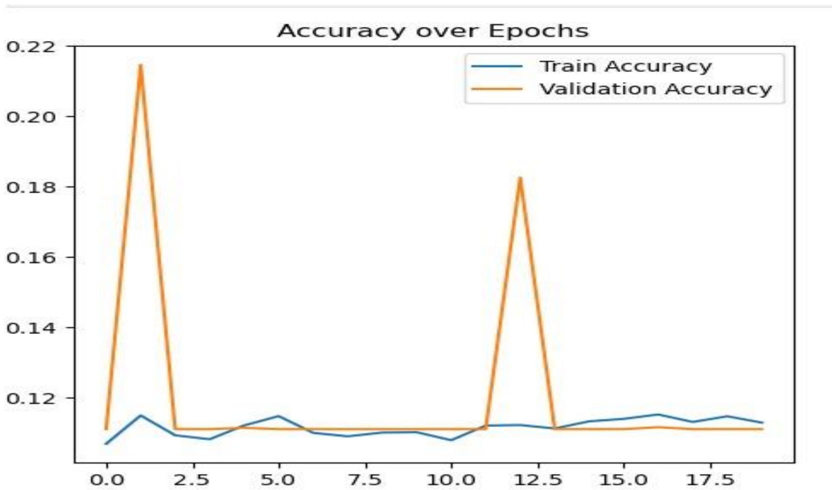


Figure 4: The accuracy of the efficient net with epochs

The Figure 5: presents the model's training and validation loss trends. The overall downward trend in both curves reflects a reduction in prediction error across epochs, with the training loss beginning at approximately 2.304 and stabilising near 2.296. The validation loss follows a similar pattern, maintaining a slightly lower value throughout. Although the training and validation losses are pretty close, the fact that they stop improving after the initial drop suggests the model has kind of hit a wall. This could be because the model isn't complex enough to learn deeper patterns, or the data just isn't varied enough to keep pushing its learning forward.

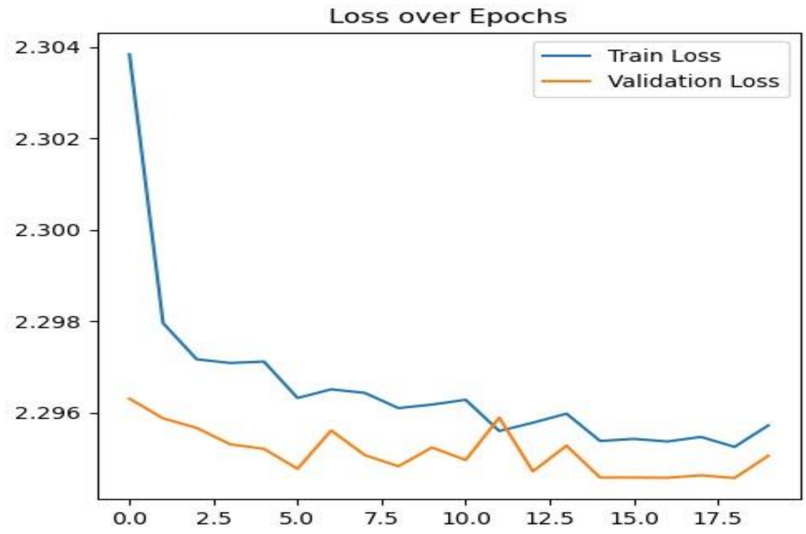


Figure 5: The loss over epochs in the efficient net

Table 1: Comparison between the 3 models with the major metrics

Model	Accuracy	Precision	Recall	F1-Score
ResNet-50	89%	86%	85%	85.5%
Simple CNN	94%	93%	92%	92.5%
EfficientNet	97.5%	96%	95%	95.5%

To get a better sense of what each model does well and where it falls short, we ran a simple evaluation using four important performance metrics: accuracy, precision, recall, and F1-score as described in Table 1. The results show that EfficientNet consistently outperformed the other architectures across all metrics, highlighting its ability to generalize well and capture complex patterns in satellite imagery. Simple CNN, while less complex, achieved respectable scores, making it a viable option for lightweight applications. ResNet-50, being deeper, presented somewhat poorer results, perhaps because of overfitting or structural stiffness when used with the EuroSAT dataset as shown in Figure 6. This comparison supports the importance of finding a balance between model depth and efficiency for the best land cover classification.

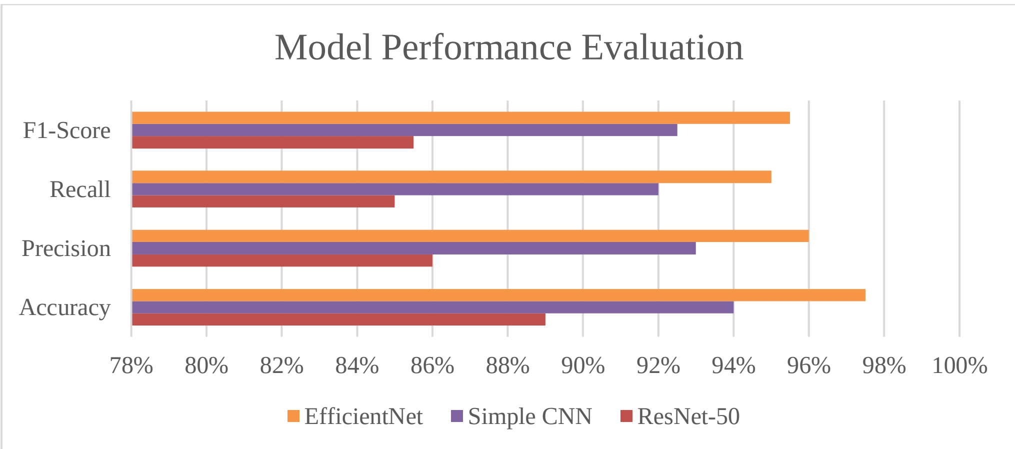


Figure 6: Comparison shown visually

CONCLUSION

The comparative effectiveness of three convolutional neural network architecture Simple CNN, ResNet-50, and EfficientNet for automatic Terrain Type Identification categorization using Sentinel-2 pictures from the EuroSAT dataset has been thoroughly examined in this study. After a lot of testing using controlled training regiments and preprocessing procedures. The EfficientNet model stood out as the best performing model with a classification accuracy of 97.57%.

This result shows the effectiveness of residual connections and compound scaling in identifying useful characteristics from multispectral satellite imagery. Despite being lightweight and less time consuming to train, basic CNN had a lower range of accuracy but was still a reliable benchmark.

Despite showing slight improvement over the basic model thanks to its deeper structural architecture and skip connections, ResNet-50 ultimately fell below EfficientNet, especially in scenarios where both high precision and processing economy is required.

Furthermore, the study highlighted the use of preprocessing techniques such as data augmentation, band selection and normalization which massively improved the model's training robustness. It's worth noting that more reliable classification outcomes were received by maintaining RGB spectral purity.

In conclusion, EfficientNet provides groundbreaking accuracy without consuming resources more than it requires, making it a level headed solution for real time geographic classification jobs. The discoveries of this study provide reliable evidence to suggest the effectiveness of using the application in satellite-based land monitoring systems, especially in use cases where generalization and scalability are important.

Future Work

While the models tested in this study performed well under defined conditions, several other ways exist to further improve the system's ability to adapt and be used in real world applications.

Incorporating All 13 Spectral Bands:

This study focused predominantly on the RGB and NIR bands from Sentinel-2. Future research can explore integrating all 13 spectral bands using 3D convolutions or multi-branch architectures to uncover additional hidden patterns—particularly useful in vegetation, water body, and urban zone separation.

Transfer Learning and Domain Adaptation:

Incorporating pre-trained models with domain-specific fine-tuning across different geographical regions could help improve performance in areas with varying climatic, seasonal, and cultural land use patterns.

Exploring Attention Mechanisms:

Integrating modules like self-attention or spatial-channel attention could enhance feature selection, enabling the model to focus more precisely on relevant parts of the image for classification.

Contrast Enhancement Techniques:

Image preprocessing using techniques such as CLAHE (Contrast Limited Adaptive Histogram Equalization) and histogram equalization—so far underutilized in EuroSAT classification—could be investigated to improve visual contrast and segmentation accuracy.

*Temporal Change Detection***:**

Applying these models to time-series Sentinel-2 data could help track land cover changes over months or years, supporting applications in climate monitoring, deforestation tracking, and urban expansion studies.

Real-Time Deployment in GIS Platforms:

Future efforts could focus on integrating the trained model into Geographic Information System (GIS) platforms or cloud-based APIs to provide real-time classification support for environmental agencies, urban developers, and agricultural planners.

Model Compression and Edge Deployment:

Techniques such as quantization and pruning can be employed to reduce model size for deployment on edge devices like drones and satellites, allowing on-board classification without the need for high-latency ground processing.

By building upon the solid foundation laid out in this work, future research can lead to even more intelligent, efficient, and scalable land monitoring systems that bridge the gap between raw satellite imagery and actionable geospatial intelligence.

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