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Comparative Study of Pretrained Models for Remote Sensing Image Classification

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Abstract
Remote Sensing (RS) image classification, particularly involving Earth Observation (EO) satellite data, presents significant challenges due to the complexity and variety of image content. This study addresses these challenges by evaluating the performance of three advanced deep learning models—DenseNet121, ResNet50, and EfficientNetB7—on the UC Merced Land Use (UCM) dataset. By leveraging pre-trained Convolutional Neural Networks (CNNs) through transfer learning, our approach effectively mitigates the issue of limited labelled data and enhances the accuracy of classification in high-resolution aerial imagery. This paper provides an in-depth study of said models, emphasizing their accuracy, precision, recall, and computing efficiency in the classification of land use domains. The findings provide insightful information about how well these various CNN architectures perform in classifying remote sensing images and lay the groundwork for further deep learning-based land use categorization research
Keywords: *Classification, High-Resolution Images, Transfer Learning, Remote Sensing, Satellite Data*

1. Introduction
The rapid development of deep learning technology has revolutionized the analysis of data in remote sensing images, providing unprecedented accuracy and efficiency in many field applications such as land cover classification, crop discovery and transformation. Remote sensing, which involves obtaining information about the Earth's surface from satellite or aerial images, presents unique challenges and opportunities for training deep models. The inherent complexity and high dimensionality of these images require sophisticated algorithms that can extract content features and make accurate predictions. Among many deep learning methods, DenseNet121, ResNet50, and EfficientNetB5 have emerged as the main candidates, each with unique features and advantages. This comparative study aims to evaluate and compare these three models to determine their effectiveness in processing data in remote sensing images. DenseNet121 was proposed by Huang et al. This design improves the extension and support of recycling materials, which is important for high-resolution tasks with complex details such as those encountered in remote sensing. Such a structure increases efficiency and improves accuracy by allowing each layer to directly connect to previous layers, thus supporting more powerful learning. An impressive architecture that has a significant impact on deep learning applications.
ResNet50, developed by He et al., introduces the concept of residual learning, where the network learns residual mappings instead of direct learning. This approach can train deep networks by reducing the degradation problems commonly encountered in deep models. The connections in ResNet50 facilitate the flow of gradients in the network, improving the performance of tasks such as object recognition and segmentation. In remote sensing, where images vary in scale and background, the ability of the model to learn complex features and handle operations at different depths is a nice result. Architecture. EfficientNetB5 is based on the concept of network scaling, which balances the width, depth, and resolution of the network to achieve a balance between accuracy and computational efficiency. The EfficientNet family uses a novel deployment strategy that improves performance and resource utilization,

making it especially suitable for remote sensing applications where processing power and memory are less of an issue. EfficientNetB5 can provide high accuracy while maintaining low cost, making it the best choice for analysing big data in remote areas. analyse content. By evaluating the performance of these models according to various metrics such as classification accuracy, computational efficiency, and performance for different images, we aim to define deep learning for remote sensing applications. The comparisons will provide insight into the strengths and limitations of each model and inform future research and practical applications in remote sensing.

2. Literature Review

Remote sensing image classification has witnessed tremendous development by incorporating deep learning techniques. As can be seen, the fusion of deep learning into satellite image classification in remote sensing will revolutionize the field: it enables automatic and rather more precise analysis of complex datasets by computing. Adegun et al. [1] investigated a comparative analysis of some deep learning models, suggesting that deeper CNNs involving more layers have exceptional behavior in dealing with heterogeneous appearance typical in high-resolution images, which are typical in large-scale satellite images. Ahmad et al. [2] presented a wide-ranging overview of the techniques to classify remote sensing images, while emphasizing challenges like multi-class classification, the need for benchmark large-scale datasets, and more efficient deep learning models. Cheng et al. [3] looked into the intersection of scene classification and deep learning and discovered the architectural innovation behind such successful techniques and how to make good use of opportunities for persisting challenges in the domain. Applications of deep learning on the specific domains were very versatile, such as its use in the automatic identification of medicinal plants based on the leaf images, by using DenseNet201 as done by Dey et al. [4-5]. While the model worked fine, there was a problem in species variability, geographical differences, and seasonal changes that still required further refinement. Guo et al. [6] introduced a channel saliency-based method known as CSG-CAM, which helps in increasing the interpretability of remote sensing image classification through dynamic channel pruning and gradient-based saliency visualizations. Gupta et al. [7] explored transfer learning with pre-trained deep learning models such as VGG19, InceptionV3, and DenseNet169, which achieved massive computational savings and robust classification performance, especially in areas where labeled datasets are minimal. Several novel frameworks and approaches have been developed to enhance classification accuracy and efficiency. Dou et al. [5] and Peng et al. [15] have integrated deep learning with multiple classifier systems in time-series remote sensing image classification. Their hybrid frameworks attained tremendous performance across datasets like AID and NWPU-RESISC45. Liu et al. [13] suggested the Object-oriented CNN, which performed better than a traditional CNN in land cover and vegetation classification, and their technique was improved by 5%. Yin et al. [20] enhanced the feature extraction and optimization technique for benchmark datasets like CIFAR-10 and CIFAR-100 using a dynamic pruning and reconstruction network, which extended DenseNet. Similarly, Wang et al. [18] added residual attention mechanisms to DenseNet to improve performance in the classification of images of power equipment with an accuracy improvement of 8.89% on datasets that include CIFAR-10. Deep learning has also been helpful in solving challenges in medical imaging and urban analysis. For example, Hasan et al. [8] showed the use of DenseNet in predicting cases of COVID-19 from CT images. The study attained a commended accuracy of 92% but was constrained by size and the necessity for visualizations. Liao et al. [11] applies DenseNet in the context of asymmetry detection in mammography, such that the model is superior compared to junior radiologists to detect lesions in the RMLO and RCC datasets. Zhao et al. [21] discussed the use of deep transfer learning for cross-city land use classification by leveraging the labeled datasets of similar regions to improve overall and average accuracy. This demonstrates the increased use of transfer learning in adapting pre-trained models to specific domains. Explainable AI and

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interpretability in remote sensing is increasingly gaining attention as researchers focus on model reliability. Ishikawa et al. [9] presented an example-based explainable AI approach, wherein similar examples from training data are presented during inference to improve user trust and validation. Similarly, Guo et al. [6] used saliency maps for visual explanations of model predictions, thus focusing on interpretability. These efforts indicate that more and more importance is being given to the understanding and justification of decisions made by models, especially in high-stakes applications such as environmental monitoring and disaster management.

Comprehensive surveys have synthesized the state of the art and identified opportunities for future research. Tombe et al. [17] analyzed advancements in deep learning architectures, frameworks, and datasets for remote sensing image scene classification, while Li et al. [12] reviewed CNNs, stacked autoencoders (SAEs), and deep belief networks (DBNs) using the UCM dataset. Their conclusions highlighted the need for integration of spectral and spatial features and robust optimization techniques. Kumar et al. [10] proved the potential of DCNN models in region classification mining with fused multi-sensor satellite data with 99.8% accuracy, which establishes a benchmark for future work. Transfer learning and data augmentation are the most critical factors in exploiting deep learning for remote sensing. Thirumaladevi et al. [16] applied transfer learning to the SIRI-WHU dataset, where they modified pre-trained networks to achieve better classification accuracy. Yang et al. [19] compared lung images of COVID-19 patients, showing the advantages of residual connections in ResNet and the efficiency of EfficientNet for small datasets. These studies jointly emphasize the transformative potential of deep learning in remote sensing image classification. However, there are also critical gaps ahead, such as scalable models, explainable frameworks, and robust methods to mitigate variability across datasets. Moving forward, hybrid approaches should continue to be explored, while novel architectures are integrated, along with a focus on interpretability, so that deep learning techniques meet the demands of diverse applications and evolving challenges.

3. Methodology

This section explains how the Keras library for deep learning is used to implement transfer learning. First, the available pre-trained models are displayed. Next, the input data is pre-processed for classification. Finally, the pre-trained model is fine-tuned to improve the output.

3.1. Datasets

The UC Merced (UCM) Land Use dataset is a popular resource in remote sensing and computer vision research, particularly for land use and land cover classification. It consists of 2,100 high-resolution aerial images, each measuring 256 x 256 pixels, divided into 21 unique land use categories with 100 images per class. To enhance the dataset's diversity and size, data augmentation techniques were applied, generating four additional variations for each original image, resulting in 500 images per class. The dataset represents a wide range of natural and human-made environments, such as "agricultural," "airplane," "baseball diamond," "beach," "buildings," "chaparral," "dense residential," "forest," "freeway," "golf course," "harbour," "intersection," "medium residential," "mobile home park," "overpass," "parking lot," "river," "runway," "sparse residential," "storage tanks," and "tennis court." With its consistent image dimensions and balanced class distribution, the UCM dataset serves as a robust platform for developing and evaluating machine learning models, particularly for image classification and land use mapping tasks. Its diverse class representation—from natural features like forests and rivers to human-made structures such as runways and storage tanks—makes it a comprehensive resource for studying various land use types in remote sensing imagery. Figure 1 shows the UCM sample database images.

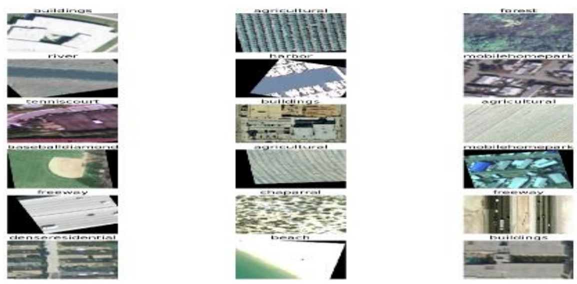

Figure 1 UCM Database Sample Images

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3.2.Architecture of ResNET50

ResNet50 is a CNN architecture known for its introduction of residual connections, which help mitigate the vanishing gradient problem and enable the training of much deeper networks. Introduced by He et al. in 2015, ResNet50 is part of the ResNet family and consists of 50 layers. Its key innovation is the residual block, where the input to a layer is added directly to the output, allowing gradients to flow more easily through the network. The architecture is organized into an initial convolution and max pooling layer, followed by four stages of convolutional blocks with residual connections. Each stage consists of several blocks, with 1x1, 3x3, and 1x1 convolutions. The network ends with a global average pooling layer, a fully connected layer, and a softmax activation for classification. ResNet50's design enables the construction of deeper and more accurate models while maintaining manageable computational complexity, making it highly effective for various image recognition tasks. Figure 2 describes Architecture of ResNet50 [11-17].

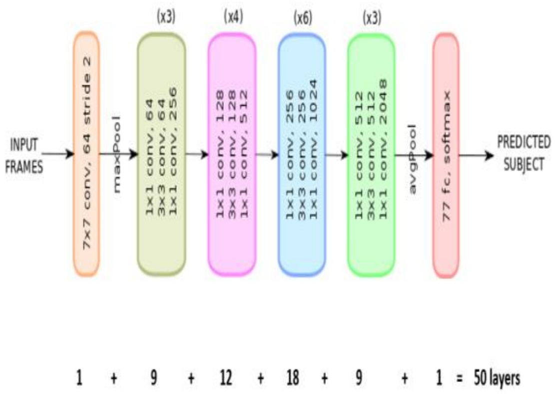

Figure 2 Architecture of ResNet50

3.3. Architecture of DenseNet121

Figure 3 Shows DenseNet121 architecture. DenseNet121 is a CNN architecture known for its dense connectivity, where each layer receives inputs from all preceding layers and provides outputs to all subsequent layers. Introduced in 2017 by Huang et al., DenseNet121 is part of the DenseNet family, designed to enhance gradient flow and feature reuse, thus reducing the vanishing gradient problem and improving parameter efficiency. The model comprises four dense blocks interspersed with transition layers that down sample feature maps. Specifically, it includes an initial 7x7 convolution followed by max pooling, then dense blocks with 6, 12, 24, and 16 layers, each separated by 1x1 convolution and 2x2 average pooling transition layers. The architecture concludes with the global average pooling and a completely connected layer with softmax activation for classification. This design maintains high performance while being computationally efficient, making DenseNet121 suitable for various image recognition tasks.

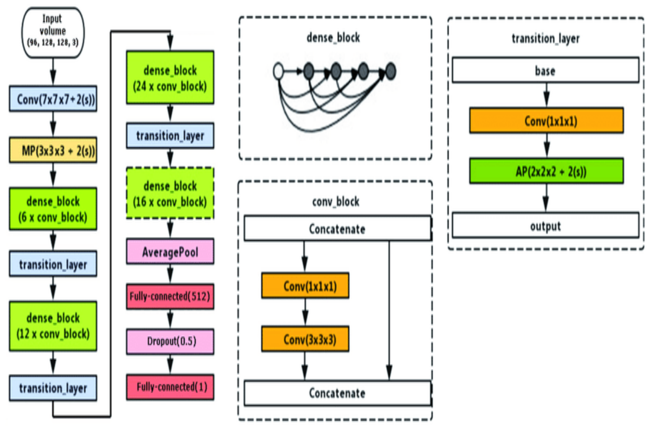

Figure 3 Architecture of DenseNet121

3.4. Architecture of EfficientNetB7

Figure 4 Architecture of EfficientNetB7

Figure 4 shows EfficientNetB7 Architecture. EfficientNetB7 is a high-performance CNN architecture that balances accuracy and efficiency through compound scaling. Introduced by Tan and Le in 2019, EfficientNetB7 is part of the EfficientNet family, which scales depth, width, and resolution systematically. This model achieves the state-of-the-art performance with lesser parameters and computational resources compared to the previous architectures. EfficientNetB7 employs a baseline network optimized with Mobile Inverted Bottleneck Convolution (MBConv) blocks and includes techniques like depth wise separable convolutions and squeeze-and-excitation optimization. The architecture is scaled up proportionally in all dimensions—layers, channels, and image resolution—to maintain efficiency. Starting with an initial 3x3 convolution and max pooling, it consists of several MBConv blocks followed by global average pooling, a fully connected layer, and a softmax activation for classification. EfficientNetB7's design offers a powerful yet resource-efficient solution for a wide range of image recognition tasks [18-21].

4. Results and Discussion

Based on their accuracy and loss values, we examine and contrast the three deep learning models—ResNet50, DenseNet121, and EfficientNetB7 in this section. EfficientNetB7 demonstrated strong performance, likely due to its architecture, which prioritizes computational efficiency while balancing network depth, width, and resolution. To assess these models' performance in image classification tasks, a specific dataset was used. With a loss of 0.1431 and an accuracy of 96.19%, the results show that EfficientNetB7 performed the best, demonstrating its proficiency in identifying significant features and generalizing well to new data. DenseNet121, in contrast, performed quite well, achieving an accuracy of 83.76% and a lower loss value of 0.6836. Its performance was noteworthy, even if it fell short of EfficientNetB7's accuracy level. This can be attributed to its dense connectivity, which promotes feature reuse across layers and reduces the number of parameters required to achieve high accuracy. However, compared to EfficientNetB7, DenseNet121 seemed less adept at managing the dataset's complexity. Despite being well-regarded for its residual connections, which enable it to handle deep architectures effectively, ResNet50 performed the worst among the three models. It achieved a lower accuracy of 70.33% and a relatively high loss value of 1.4299. This suggests that ResNet50 may not be the best choice for this dataset or may require additional fine-tuning to improve its performance. While ResNet50 is known for its resilience and effectiveness in various image classification tasks, its results in this case indicate limitations with this dataset. Overall, the outcomes highlight the varying performance of different models, with EfficientNetB7 emerging as the most successful model for this classification task. Table 1 shows the performance of transfer learning models of land use scene data set.

Table 1 Comparison of Transfer Learning Models on Land use Scene Dataset

Model	Loss	Accuracy
ResNet50	1.4299	0.7033
DenseNet121	0.6836	0.8376
EfficientNetB7	0.1431	0.9619

There is noticeable rise in the performance of all three models—ResNet50, DenseNet121, and EfficientNetB7—on the picture classification test after fine-tuning them by making the final three layers of each model trainable while maintaining the remaining layers frozen. By making these deliberate changes, each model was able to concentrate on honing the most specialized layers for the dataset, maximizing their capacity to extract important features without overfitting to the training set. By fine-tuning the upper layers of the model, the models were able to more precisely respond to the unique features of the dataset, which produced better classification results. After using this consistent fine-tuning technique, EfficientNetB7 demonstrated the most performance gains, with its accuracy increasing to 97.43% and its loss falling to 0.0876. Fine-tuning the final three layers improved the model's design, which effectively strikes a balance between computational power and network complexity. This allowed the model to learn from the data more effectively. Through additional feature extraction improvements, EfficientNetB7 emerged as the most

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accurate model in this comparison, demonstrating its continued aptitude for challenging picture classification tasks. Following the fine-tuning, DenseNet121 also saw notable gains, with an accuracy increase to 97.19% and a loss value decrease to 0.0892. Its architecture, with its extensive connectivity, encourages feature reuse, which can be especially useful when training just a few layers.

Table 2 Comparison of Fine-Tuned Transfer Learning Models on Land use Scene Dataset

Model	Loss	Accuracy
ResNet50	0.2246	0.9357
DenseNet121	0.0892	0.9719
EfficientNetB7	0.0876	0.9743

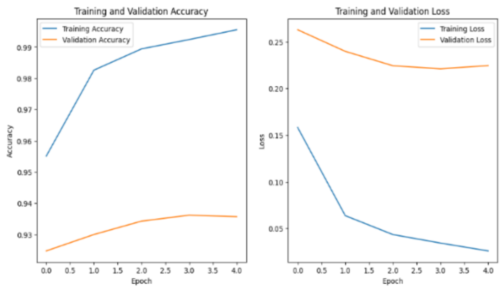

Figure 5 Training and Validation Graphs for Resnet50

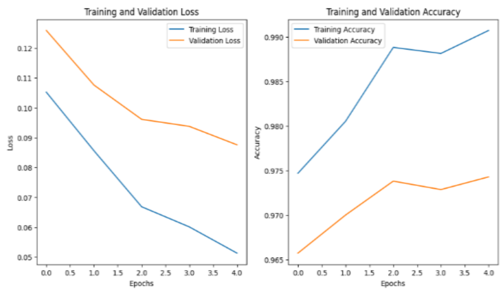

Figure 6 Training and Validation Graphs for EfficientNetB7

Figure 7 Training and Validation Graphs for DenseNet121

DenseNet121's ability to focus on the most pertinent features for this dataset was demonstrated by fine-tuning the final three layers, indicating the network's flexibility and potential for high accuracy. Using the same fine-tuning procedure, ResNet50's performance was significantly improved, yielding an accuracy of 93.57% and a loss of 0.2246. Even though it didn't perform as accurately as DenseNet121 and EfficientNetB7, the gains show how important it is to train specific layers and selectively unfreeze them to better adjust to the characteristics of the dataset. This result indicates that although the architecture of ResNet50 is robust by design, it can be made competitive for a variety of picture classification applications by fine-tuning individual layers to improve performance noticeably.

4.1. Performance Metrics.

The performance of deep learning models in image classification is generally evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-score. These metrics are explained as follows: Accuracy represents the ratio of correctly predicted instances to the total number of instances. It is calculated using the formula: Accuracy = (TP + TN) / (TP + TN + FP + FN) where TP stands for True Positives, TN for True Negatives, FP for False Positives, and FN for False Negatives. F1-Score is the harmonic mean of Precision and Recall, offering a balanced evaluation by considering both false positives and false negatives. It is calculated as: F1-Score = 2 × (Precision × Recall) / (Precision + Recall). The Figures 5, 6, and 7, describes the accuracy and loss which show the performance measures and offer further information. Figure 6 shows how EfficientNetB7 performs better than DenseNet121 across the board in all criteria. Recall (or Sensitivity) measures the proportion of actual positives correctly identified by the model. It is defined as: Recall = TP / (TP + FN). Precision measures the fraction of correctly predicted positive instances over the total predicted positives. It is calculated as: Precision = TP / (TP + FP) The Confusion Matrix provides a comprehensive analysis by showing the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This matrix

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illustrates the performance of a classification model by representing all possible combinations of actual and predicted outcomes. positive instances over the total predicted positives. It is calculated as: Precision = TP / (TP + FP). The Confusion Matrix provides a comprehensive analysis by showing the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This matrix illustrates the performance of a classification model by representing all possible combinations of actual and predicted outcomes.

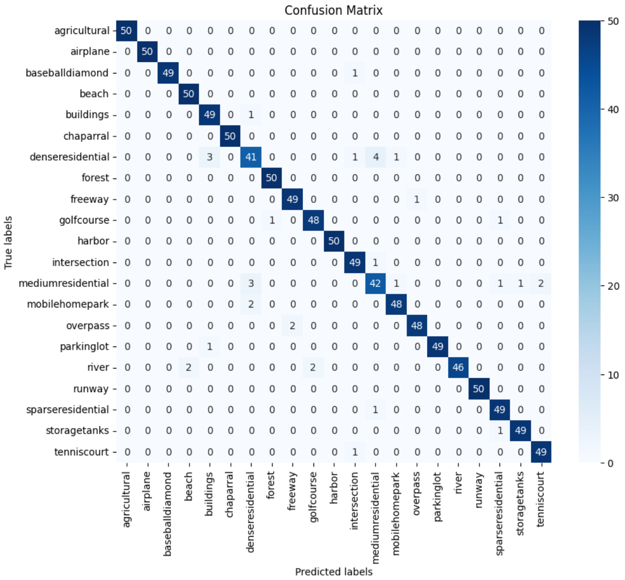

Figure 8 **Confusion Matrix for Resnet50**

4.2 Model performance on UC Merced Dataset

The performance metrics of ResNet50, DenseNet121, and EfficientNetB7, encompassing accuracy, precision, recall, and F1-score, are summarized in Table 3. The two networks with the greatest scores are DenseNet121 and EfficientNetB7. EfficientNetB7 slightly outperforms DenseNet121 in terms of accuracy (0.9667 vs. 0.9610) and F1-score (0.9664 vs. 0.9609). Although ResNet50 is doing admirably, its metrics are marginally worse than those of DenseNet121 and EfficientNetB7. Confusion matrices and classification outputs are shown in Figures 9 and 10, which demonstrate how robust and well-generalizing DenseNet121 and EfficientNetB7 are by accurately classifying most data with little misclassification. This uniform performance across several displays supports Table 3's numerical data, shown in Figure 8, 11 to 13.

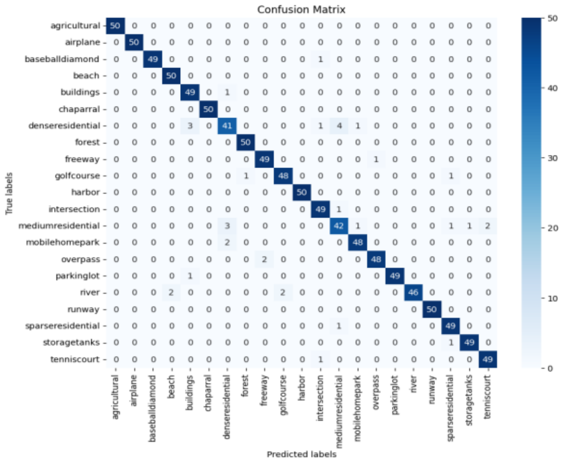

Figure 9 **Confusion Matrix for Densenet121**

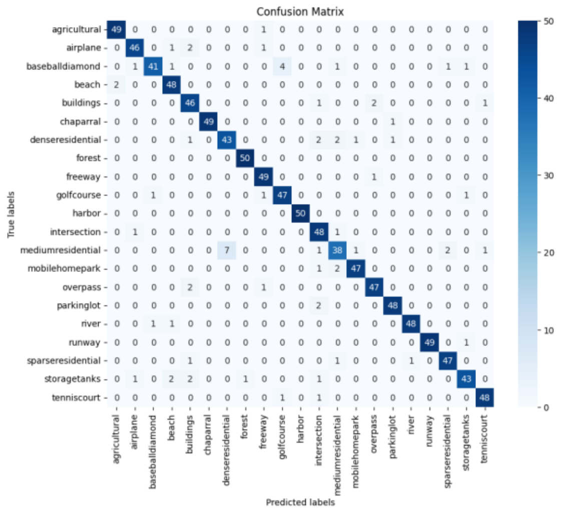

Figure 10 **Confusion Matrix for Resnet50**

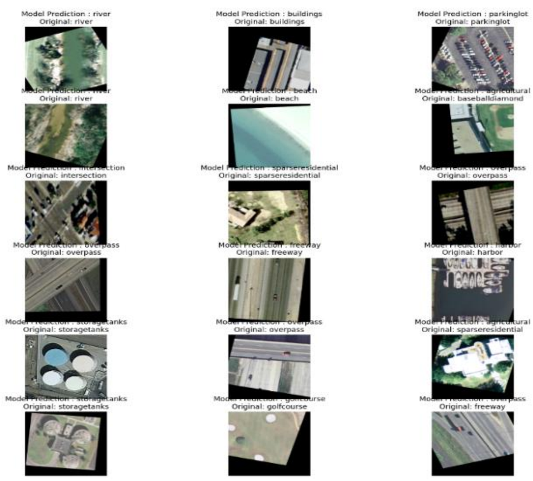

Figure 11 **Output Comparison for DenseNet121**

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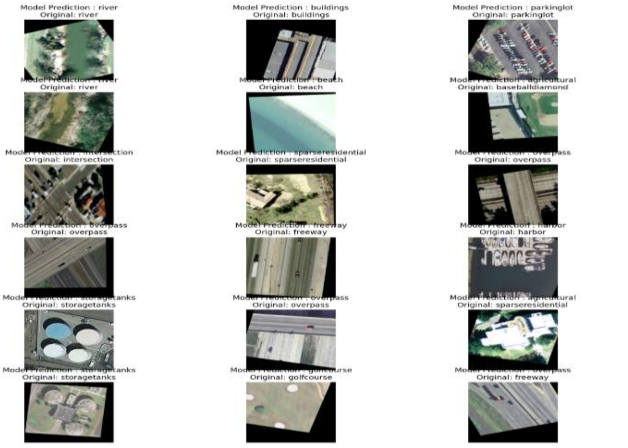

Figure 12 Output Comparison for EfficientNetB7

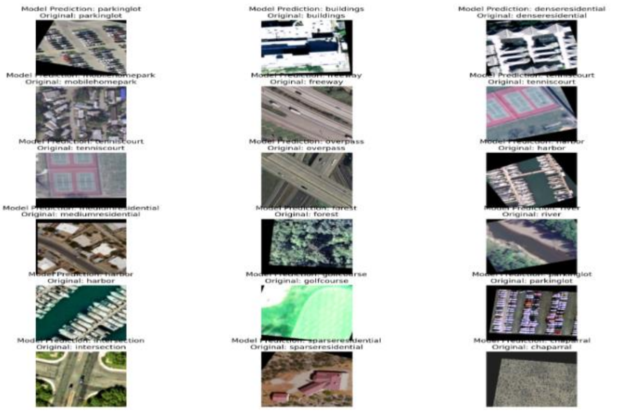

Figure 13 Output Comparison for Resnet50

Table 3 Comparison of Fine-Tuned Transfer Learning Models on Land use Scene Dataset

Model	Accuracy	Precision	Recall	F1-Score
ResNet50	0.9343	0.9352	0.9343	0.9340
DenseNet121	0.9610	0.9622	0.9610	0.9609
EfficientNet B7	0.9609	0.9666	0.9667	0.9664

Conclusion

To sum up, Resnet, Densenet, and EfficientNet are important turning points in the development of deep convolutional neural network designs, each bringing unique ideas to bear on issues with feature reuse, parameter efficiency, and training. Resnet's residual connections, which help to reduce the vanishing gradient problem and make it possible to train very deep networks, revolutionized the field of deep learning. Its skip connections increase feature learning across a range of computer vision tasks and improve information flow. With its tightly connected layers, Densenet reduces parameters dramatically while improving gradient flow and feature reuse. More compact models with richer feature representations and greater network capacity utilization are produced by this approach. By using compound scaling to balance model size, depth, and width holistically, EfficientNet achieves the state-of-the-art performance with fewer parameters. Setting the standard for resource-efficient deep learning, it provides scalability under a variety of computing limitations. When taken as a whole, these architectures have improved the field, and their breakthroughs keep neural network research moving forward. The next generation of deep learning models will probably be developed by building on the ideas of Resnet, Densenet, and EfficientNet in future research, shown in Table 3.

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