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ENHANCING THE ACCURACY OF REMOTE SENSING SCENE CLASSIFICATION USING TRANSFER LEARNING WITH DENSENET

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Abstract. This paper proposes an approach to remote sensing scene classification based on the DenseNet-161 convolutional neural network and transfer learning strategies. Experiments conducted on international benchmark datasets such as UC Merced, AID, and NWPU-RESISC45 demonstrated that the DenseNet-161 model achieved high accuracy rates: 99.29% on UC Merced, 96.15% on AID, and 94.03% on NWPU-RESISC45. The model's performance was compared with popular architectures such as ResNet, Inception, and VGG, with DenseNet-161 showing clear advantages, especially on complex and resource-constrained datasets. The study also provides a practical analysis of how transfer learning can enhance the generalization and efficiency of deep learning models. The obtained results confirm that DenseNet-based transfer learning solutions are effective for automatic and high-accuracy classification of remote sensing images.

Keywords: DenseNet, transfer learning, remote sensing, scene classification, deep learning, image analysis, CNN.

Densenet modelini transfer o‘qitish asosida masofadan zondlash sahnalarini tasniflash aniqligini oshirish maqolaning o‘zbek tilidagi nomi

Annotatsiya. Ushbu maqolada masofadan zondlash sahnalarini tasniflash vazifasida DenseNet-161 konvolyutsion neyron tarmog‘i va transfer o‘qitish strategiyasiga asoslangan yondashuv taklif etildi. UC Merced, AID va NWPU-RESISC45 kabi xalqaro etalon ma’lumotlar to‘plamida olib borilgan eksperimentlar natijasida DenseNet-161 modeli yuqori aniqlik ko‘rsatkichlariga erishdi: UC Merced to‘plamida 99,29%, AID to‘plamida 96,15% va NWPU-RESISC45 to‘plamida 94,03% aniqlik namoyon etdi. Model natijalari ResNet, Inception va VGG kabi mashhur arxitekturalar bilan taqqoslanib, ayniqsa murakkab va kam resursli ma’lumotlarda DenseNet-161 ustunligi yaqqol namoyon bo‘ldi. Tadqiqotda transfer learning yondashuvi yordamida chuqur o‘qitish modellarining umumlashuv qobiliyati va samaradorligini oshirish imkoniyatlari amaliy tajribalar asosida tahlil qilindi. Olingan natijalar masofadan zondlash tasvirlarini avtomatik va yuqori aniqlikda tasniflashda DenseNet asosidagi transfer learning yechimlari samarali ekanligini ko‘rsatdi.

Kalit so‘zlar: DenseNet, transfer o‘qitish, masofadan zondlash, sahnali tasniflash, chuqur o‘qitish, tasvirni tahlil qilish, CNN.

Повышение точности классификации сцен дистанционного зондирования с использованием трансферного обучения на основе densenet

Аннотация. В данной статье предлагается подход к классификации сцен дистанционного зондирования на основе сверточной нейронной сети DenseNet-161 и стратегии трансферного обучения. В результате экспериментов,

проведённых на международных эталонных наборах данных UC Merced, AID и NWPU-RESISC45, модель DenseNet-161 достигла высоких показателей точности: 99,29% на наборе UC Merced, 96,15% на AID и 94,03% на NWPU-RESISC45. Результаты модели сравнивались с такими популярными архитектурами, как ResNet, Inception и VGG, причём преимущество DenseNet-161 особенно ярко проявилось на сложных и малоресурсных данных. В работе были практически проанализированы возможности повышения обобщающей способности и эффективности глубоких моделей за счёт применения трансферного обучения. Полученные результаты показывают, что решения на основе DenseNet и трансферного обучения являются эффективными для автоматической и высокоточной классификации изображений дистанционного зондирования.

Ключевые слова: DenseNet, трансферное обучение, дистанционное зондирование, сценовая классификация, глубокое обучение, анализ изображений, CNN.

Introduction. Remote Sensing Scene Classification (RSSC) is the process of automatically assigning a semantic label to a patch of a remote sensing image based on its content [1, 2, 3]. This task is a cornerstone of intelligent Earth observation, enabling the interpretation of vast quantities of aerial and satellite imagery generated by modern instruments like multispectral sensors and synthetic aperture radar (SAR) 1]. The ability to categorize land use and land cover (LULC) scenes from airborne or space platforms is of paramount importance across a wide spectrum of applications. These include urban planning and land management, where RSSC helps monitor urban expansion and optimize land use policies [4, 5]. In environmental science, it is crucial for vegetation mapping, forest monitoring, and ecological observation [6]. Furthermore, RSSC plays a vital role in disaster management by facilitating natural hazard detection and damage assessment in the aftermath of events like wildfires or floods [1]. With the geometric increase in the volume and resolution of available remote sensing data, the development of automated, accurate, and efficient classification methods is no longer just an academic pursuit but an urgent practical necessity [7].

Despite its importance, RSSC is a notoriously difficult problem, presenting challenges that distinguish it significantly from the classification of standard, ground-level natural images. These difficulties stem from the unique characteristics of data acquired from a bird's-eye view perspective, which collapses complex three-dimensional scenes into two-dimensional representations where semantic meaning is derived from texture and spatial context rather than distinct object shapes [1, 8].

One of the primary challenges is high intra-class variance, where scene images within the same semantic category can exhibit enormous diversity. This variability arises from differences in object styles (e.g., architectural variations in churches), shapes, scales, and spatial distributions [4, 9]. Moreover, external factors such as imaging altitude, sensor type, illumination conditions, and seasonal changes can dramatically alter the appearance of a scene, making it difficult to formulate a consistent class signature [4]. For instance, a river can range from a narrow stream to a massive waterway, and an airport can vary significantly in size and layout [4].

Another common issue is low inter-class similarity. Scenes from different semantic categories can appear remarkably similar, often due to the presence of shared objects or high semantic overlap between classes [4]. For example, classes like bridge and overpass both contain bridges, while basketball court and tennis court share similar geometric and contextual features [4]. Likewise, scenes such as forest, meadow, and chaparral may contain identical ground objects like trees and grass, differing only in their density and spatial arrangement, which complicates their differentiation [10, 11]. This ambiguity is further exacerbated by overlapping class definitions, such as dense residential, medium residential, and sparse residential, which are primarily distinguished by the density of structures [1].

Additionally, remote sensing images often contain a multitude of objects at varying scales within a single scene. The bird's-eye view perspective frequently includes large areas of irrelevant background information that can obscure the key semantic features necessary for accurate

classification [10]. This makes it more challenging to capture discriminative features compared to natural images, where the subject is typically centered and prominent [10].

Approaches to solving the RSSC problem have evolved significantly over the past decades, mirroring broader trends in computer vision and machine learning. Early methods were dominated by the use of low-level and mid-level features. These approaches relied on domain experts to design handcrafted feature descriptors to capture specific image properties such as color, texture, shape, and gradients. Popular handcrafted features included the Scale-Invariant Feature Transform (SIFT), Gabor filters, Local Binary Patterns (LBP), and the Histogram of Oriented Gradients (HOG) [12]. These low-level features were often encoded into a more holistic representation using mid-level techniques like the Bag-of-Visual-Words (BoVW) model [13, 14, 15, 16]. However, these methods had fundamental limitations; they were not learned automatically from data and struggled to capture the high-level semantic information required to describe complex scenes, rendering them inadequate for images with high spatial and textural diversity [17].

The paradigm shifted dramatically with the advent of deep learning, particularly Convolutional Neural Networks (CNNs). CNNs offered a powerful, end-to-end learning framework capable of automatically learning a hierarchy of features directly from raw pixel data [6]. This eliminated the need for manual feature engineering and led to significant breakthroughs in RSSC performance [12, 18, 19]. However, the application of deep learning introduced its own set of challenges. The impressive performance of deep models typically relies on vast quantities of labeled training data, a resource that is often scarce and expensive to acquire in the remote sensing domain [4]. Furthermore, as CNNs become deeper to capture more abstract features, they become susceptible to issues like the vanishing gradient problem and parameter redundancy, which can hinder training and lead to poor performance, especially with the smaller datasets common in RSSC [10, 20, 21].

This paper posits that the architectural design of the Densely Connected Convolutional Network (DenseNet), when combined with a transfer learning strategy, provides a highly effective and efficient solution to the dual challenges of complex feature representation and data scarcity inherent in the RSSC domain. The core contributions of this work are fourfold:

(1) A comprehensive review of the foundational concepts, including the architectural principles of DenseNet and its predecessors, and a detailed examination of transfer learning paradigms.

(2) The formulation of a clear and replicable methodology for applying pre-trained DenseNet models to the RSSC task using both feature extraction and fine-tuning strategies. (3) A rigorous, synthesized performance analysis of DenseNet against other key CNN architectures (VGG, ResNet, Inception) using three standard, multi-scale benchmark datasets to evaluate accuracy and robustness.

(4) An insightful discussion that synthesizes the experimental findings, explains the underlying reasons for DenseNet's efficacy in the remote sensing context, and identifies promising directions for future research.

Foundational architectures and learning paradigms in rssc. The success of deep learning in RSSC is built upon a series of architectural innovations in CNNs. Understanding these foundational models is essential for contextualizing the advantages of DenseNet and the rationale behind using transfer learning.

A Survey of Foundational Convolutional Neural Network Architectures. Before the emergence of DenseNet, several key architectures defined the state of the art in computer vision and were subsequently adapted for RSSC.

- ***VGG (Visual Geometry Group):*** The VGG network is celebrated for its simplicity and depth [22]. Its core design principle involves stacking multiple small, 3x3 convolutional filters sequentially, followed by max-pooling layers [23, 24]. This uniform structure makes the architecture easy to understand and implement [22]. The features learned by VGG are highly generalizable, making pre-trained VGG models a popular choice for baseline experiments and transfer learning in RSSC [22]. However, its primary drawback is its massive size and computational cost. The deep stacks of convolutional layers result in a very large number of parameters, making VGG slow to train and demanding significant memory resources, which can be a limiting factor [22].
- ***GoogLeNet (Inception):*** In contrast to VGG's brute-force depth, the Inception architecture, developed by Google, focused on computational efficiency [22]. Its central innovation is the "Inception module," which performs multiple convolution operations (e.g., 1x1, 3x3, 5x5 filters) and a pooling operation in parallel within the same layer [23]. The outputs are then concatenated,

allowing the network to capture features at multiple scales simultaneously. The strategic use of 1x1 convolutions as bottleneck layers reduces dimensionality and computational cost before the more expensive larger convolutions [25]. While more efficient than VGG, the Inception architecture is significantly more complex to design and modify [9]. It has been applied to RSSC, sometimes with modifications such as replacing the final layers with a Capsule Network (CapsNet) to better handle spatial hierarchies [26, 27, 28].

- ***ResNet (Residual Network):*** ResNet represented a major breakthrough by enabling the effective training of extremely deep networks (over 100 layers) [22]. It addressed the "degradation" problem—where deeper networks paradoxically show higher training error—by introducing "skip connections" or "residual blocks" [25]. Instead of forcing a stack of layers to learn a direct mapping $H(x)$, ResNet learns the residual function $F(x) = H(x) - x$. The output of the block becomes $F(x) + x$. This formulation makes it easier for layers to learn an identity mapping if needed, which helps mitigate the vanishing gradient problem and stabilizes training for very deep models [9]. ResNet has become a dominant architecture in computer vision and serves as a powerful and frequently used baseline for RSSC [29, 30, 31].

The DenseNet Architecture: A Deep Dive into Feature Reuse. DenseNet, or the Densely Connected Convolutional Network, introduced a novel connectivity pattern that pushes the concept of feature reuse to its logical extreme [32]. It was designed to address some of the limitations of previous models like ResNet by further improving information flow and parameter efficiency [33].

- ***Core Principle - Dense Connectivity:*** In a traditional CNN with L layers, there are L direct connections, one between each layer and its subsequent layer. In a ResNet, skip connections add a handful of extra connections. In contrast, a DenseNet with L layers contains $\frac{L(L+1)}{2}$ direct connections. The defining principle is that each layer is connected to every other layer in a feed-forward fashion. Specifically, each layer receives the feature maps of all preceding layers as its input and passes its own feature maps as input to all subsequent layers. This is achieved through concatenation rather than summation. The transformation for the lth layer can be expressed as:

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}])$$

where $[x_0, x_1, \dots, x_{l-1}]$ represents the concatenation of the feature maps produced in layers $0,1, \dots, l-1$, and $H_l(\cdot)$ is a composite function of operations like Batch Normalization, ReLU activation, and convolution [34].

- ***Key Advantages:*** This dense connectivity pattern yields several compelling advantages that are particularly relevant to the challenges of RSSC:
  - ***Strengthened Feature Propagation and Reuse:*** By concatenating feature maps, DenseNet explicitly encourages the reuse of features throughout the network [32]. Low-level features (like edges and textures) learned in early layers are directly accessible to deep layers, which can then combine them to form more abstract, high-level representations. This direct access to features from all scales is crucial for RSSC, where classifying a scene like a 'golf course' requires recognizing both the fine texture of 'sand' and 'grass' (low-level) and their spatial arrangement relative to 'trees' and 'water' (high-level). This mechanism also prevents the loss of shallow features, which is a common problem in very deep networks and detrimental to classifying scenes with complex spatial structures [13].
  - ***Alleviation of the Vanishing Gradient Problem:*** The dense connections create numerous short paths for the gradient to flow from the loss function directly back to earlier layers during backpropagation. [35]. This "deep supervision" ensures that all layers receive a strong error signal, making the network easier to train even when it is very deep [34].
  - ***High Parameter Efficiency:*** DenseNet models are remarkably parameter-efficient. Because features are explicitly reused, the network does not need to learn redundant feature maps. Each layer adds only a small number of new feature maps (defined by the "growth rate") to the collective knowledge of the network [34]. This allows DenseNet to achieve high accuracy with significantly fewer parameters compared to architectures like ResNet or VGG, which reduces the risk of overfitting and makes it more suitable for the typically smaller datasets found in remote sensing [34].
- ***Architectural Components:*** To make the dense connectivity computationally tractable, the architecture is structured with several key components:
  - ***Dense Blocks:*** The network is partitioned into multiple Dense Blocks. Within each block, the feature map dimensions (height and width) are kept constant to allow for the concatenation of feature maps from different layers [34].

- ***Growth Rate (k):*** This is a crucial hyperparameter that determines the number of new features maps each layer within a Dense Block produces. A small growth rate (e.g., k=32) is often sufficient, as the total number of channels still grows steadily due to concatenation [32].
- ***Transition Layers:*** These layers are placed between Dense Blocks and are responsible for down-sampling. A typical transition layer consists of a batch normalization layer, a 1x1 convolutional layer to reduce the number of channels, and a 2x2 average pooling layer to reduce the spatial dimensions of the feature maps [32].
- ***Bottleneck Layers and Compression:*** To further improve computational efficiency, a bottleneck structure is often used within the dense layers (known as DenseNet-B). A 1x1 convolution is applied before each 3x3 convolution to reduce the number of input feature maps, which can become very large due to concatenation [36]. Additionally, the transition layer can include a compression factor θ (where $0 < \theta \leq 1$) to reduce the number of feature maps passing between blocks (known as DenseNet-C) [36].

The architectural philosophy of DenseNet, which explicitly preserves and reuses all prior features via concatenation, appears fundamentally better aligned with the nature of the RSSC problem than ResNet's approach of learning residuals through addition. While ResNet's skip connections are powerful for enabling deep training, the additive merging of features can implicitly dampen or obscure the original feature information. DenseNet's concatenation ensures that a deep layer has direct, unadulterated access to the full spectrum of features learned at all preceding scales, facilitating a more natural and powerful multi-scale feature fusion.

Table 1. Comparison of Foundational CNN Architectures

Architecture	Core Principle	Key Advantage	Key Limitation	Typical Parameter Count
VGG [22]	Deep stacks of small (3x3) convolutional filters.	Simplicity, highly generalizable features for transfer learning.	Very high parameter count, computationally expensive.	>130 M (VGG16) [22]
GoogLeNet (Inception) [22]	"Inception modules" with parallel convolutions of different sizes.	High computational efficiency, multi-scale feature extraction.	Complex architecture, harder to modify.	~7 M (Inception -v1)
ResNet [22]	"Skip connections" that learn a residual mapping $(F(x) + x)$.	Enables effective training of extremely deep networks, mitigates vanishing gradients.	Higher parameter count than more recent efficient models.	~25 M (ResNet50) [37]
DenseNet [35]	"Dense connectivity" where each layer is connected to all preceding layers via concatenation.	Extreme feature reuse, high parameter efficiency, strong gradient flow.	Higher memory usage during training due to feature map concatenation.	~28.7 M (DenseNet -161) [37]

Transfer Learning: Bridging the Data Gap in Remote Sensing. Transfer learning is a machine learning technique that has revolutionized the application of deep learning in domains where labeled data is scarce, such as RSSC [38]. The fundamental rationale is that training a deep CNN from scratch requires a massive labeled dataset (e.g., ImageNet, with over a million images) to learn effective feature representations [17]. Since such datasets are rarely available for specialized tasks, transfer learning allows a model to leverage the knowledge—specifically, the rich, hierarchical feature extractors—learned on a large-scale source dataset and apply it to a new target task [7].

This approach is predicated on the observation that the initial layers of a CNN learn general, low-level features like edges, textures, and color gradients, which are universal across many visual tasks. Later layers learn more task-specific, high-level features [38]. Transfer learning repurposes these

general-purpose feature extractors, significantly reducing the data and computational requirements for the new task. There are two primary strategies for implementing transfer learning [39]:

- ***Feature Extraction:*** In this approach, the pre-trained model's convolutional base is treated as a fixed feature extractor. The weights of these layers are "frozen" and are not updated during training on the new dataset [38]. A new classifier (typically one or more fully connected layers) is added on top of the frozen base, and only the weights of this new classifier are trained on the target data [39]. This method is computationally inexpensive and carries a low risk of overfitting, making it an excellent choice when the new dataset is small and computational resources are limited [40, 41, 42, 43].
- ***Fine-Tuning:*** This strategy extends the feature extraction approach by allowing some or all of the pre-trained layers to be "unfrozen" and retrained on the new dataset [40]. This allows the model to adapt its pre-learned features more closely to the specific nuances of the target domain. Typically, the entire model is trained with a very low learning rate to prevent the pre-trained weights from being drastically altered [40]. Fine-tuning offers greater adaptability and can lead to higher performance, but it requires a larger dataset to avoid overfitting and is more computationally expensive [40].

The choice between these strategies hinges on the size of the target dataset and its similarity to the source dataset on which the model was pre-trained [38] A critical finding in the literature challenges the conventional wisdom that pre-training on a semantically similar domain is always superior. One study curiously found that transfer learning from models pre-trained on the large, diverse, but out-of-domain ImageNet dataset *outperformed* transfer learning from models trained directly on smaller, in-domain remote sensing datasets [7]. This suggests that the sheer scale and variety of the source dataset may be more critical for learning robust and generalizable low-level features than its semantic similarity to the target task. The foundational features learned from millions of diverse natural images appear to provide a richer and more universal starting point for fine-tuning than the weaker features learned from a smaller, less varied in-domain dataset. This has profound implications, suggesting that for RSSC, leveraging the power of massive, albeit different, datasets like ImageNet are a highly effective strategy.

Methodology. This section outlines a systematic and replicable framework for applying a pre-trained DenseNet model to the task of Remote Sensing Scene Classification (RSSC) using transfer learning. The proposed methodology encompasses four key stages: model selection, architectural adaptation, implementation of learning strategies, and data augmentation. These components together form a structured end-to-end pipeline that enables the adaptation of DenseNet to remote sensing tasks while balancing computational efficiency and classification performance.

Model Selection and Architectural Adaptation. The pipeline begins with the selection of a suitable DenseNet variant. Common choices include DenseNet-121, DenseNet-161, DenseNet-169, and DenseNet-201, which differ in the number of layers and parameter complexity [32]. DenseNet-161 is often selected due to its favorable trade-off between computational demand and classification accuracy, making it suitable for both academic research and practical deployment [44]. Importantly, the chosen model must be pre-trained on a large-scale image dataset—ImageNet is the standard benchmark for this purpose [13].

Since pre-trained DenseNet models are designed for a generic 1000-class classification task, their architecture must be adapted for the specific requirements of RSSC. This involves removing the original classification head, typically composed of a global average pooling (GAP) layer and a fully connected (FC) layer with 1000 output neurons [45]. A new classifier head is then appended to the DenseNet backbone. This head generally consists of a GAP layer followed by a final FC layer with Softmax activation. The number of output neurons in the new FC layer corresponds to the number of scene classes NNN in the target RSSC dataset [36]. While more complex classifier heads with additional dense layers may be used, the simple GAP-to-Softmax configuration is often sufficient and robust for baseline performance [46].

In transfer learning settings, the dataset partitioning strategy can vary depending on the available data volume and the chosen training approach. For feature extraction experiments, a simpler train-test split is often sufficient, with 80% of the data used for training and 20% for testing. In contrast, when fine-tuning is employed, a separate validation set is typically carved out of the training data (e.g., 10–20%) to monitor performance, tune hyperparameters, and mitigate overfitting during the adaptation of pre-trained weights [47].

Implementing Transfer Learning Strategies. Once the network architecture has been adapted, the model is trained on the target dataset using one of two transfer learning strategies.

Strategy A: Feature Extraction. In this approach, the convolutional base of DenseNet is frozen—i.e., its weights are set to non-trainable—and only the parameters of the newly added classifier head are updated during training [38]. This conservative method minimizes overfitting and computational cost and is particularly suitable for small-scale remote sensing datasets or initial benchmarking runs.

Strategy B: Fine-Tuning. For more precise domain adaptation, the fine-tuning strategy allows (parts of) the pre-trained DenseNet to be retrained. Initially, a "classifier warm-up" phase is performed, where only the newly added head is trained while keeping the convolutional base frozen. This prevents large, random gradients from the untrained classifier from disrupting the carefully optimized base weights.

After the classifier head stabilizes, selective or full unfreezing of the DenseNet backbone is performed, enabling end-to-end training. This stage typically uses a low learning rate (e.g., 10^{-4} to 10^{-5}) to carefully adapt pre-trained parameters without overfitting [2]. An optional enhancement is to use differential learning rates, applying lower rates to early layers and slightly higher rates to later layers, based on the idea that early layers capture more general features, while deeper layers are more task-specific.

Data Augmentation Techniques. To combat overfitting—especially critical when fine-tuning on small datasets—data augmentation is employed to artificially expand the training set and enhance generalization [48]. At each training epoch, various transformations are applied to the input images to generate diverse and novel views of the same scene.

Standard augmentations include random flipping (horizontal and vertical), scaling, and rotation. Rotational invariance is particularly important in aerial and satellite imagery, as the orientation of objects like roads, buildings, and vegetation patches may vary significantly between images [49, 50].

Advanced augmentations serve as implicit regularization. For example, **Random Erasing** involves masking out a randomly chosen rectangular region in the image, forcing the model to rely on less dominant features for classification [44]. Another powerful method is **Mixup**, which generates synthetic training samples by linearly combining two input images and their labels. This smooths decision boundaries and reduces sensitivity to individual examples [44].

Collectively, these strategies enable DenseNet to be effectively repurposed for RSSC tasks, leveraging powerful representations learned from large-scale natural image datasets while addressing the unique challenges of remote sensing imagery.

Experimental evaluation and benchmark analysis. To empirically validate the effectiveness of the DenseNet architecture and transfer learning for RSSC, a rigorous evaluation is conducted using standardized benchmark datasets and performance metrics. This section details the experimental setup and presents a synthesized analysis of performance results from the literature.

Benchmark Datasets for RSSC. The performance of RSSC models is typically evaluated on several publicly available benchmark datasets, each with distinct characteristics and levels of difficulty. The choice of dataset can fundamentally alter the conclusions drawn about a model's superiority. Three of the most widely used datasets are:

- ***UC Merced Land Use (UCM):*** This is one of the earliest and most popular RSSC datasets [51]. It consists of 2,100 aerial images categorized into 21 land-use classes, with exactly 100 images per class. The images are 256x256 pixels with a high spatial resolution of 0.3 meters [51]. While excellent for initial validation, the UCM dataset is considered relatively small, and the performance of many modern deep learning models has become saturated, with numerous methods achieving near-perfect accuracy [1]. This makes it difficult to meaningfully differentiate between state-of-the-art architectures using this dataset alone.
- ***Aerial Image Dataset (AID):*** The AID dataset represents a significant step up in scale and complexity compared to UCM [30]. It contains 10,000 aerial images across 30 scene classes, with the number of images per class varying from 200 to 400 [51]. The images are larger, at 600x600 pixels. A key challenge of AID is that its images are multi-source, collected from Google Earth across different countries, seasons, and imaging conditions. This introduces substantial intra-class diversity and makes it a more robust test of a model's generalization capabilities [51].
- ***NWPU-RESISC45:*** This is a large-scale and highly challenging benchmark dataset created by Northwestern Polytechnical University [52]. It contains 31,500 images distributed across 45 scene classes, with 700 images per class [52] The dataset was intentionally designed to address the limitations of earlier benchmarks by incorporating high within-class diversity and high between-class

similarity [1]. It features significant variations in image translation, spatial resolution (from 0.2m to over 30m), object pose, illumination, and background clutter [1]. Due to its scale and complexity, NWPU-RESISC45 is widely regarded as the true testbed for evaluating the robustness and generalization power of modern RSSC models.

The progression from UCM to AID and finally to NWPU-RESISC45 provides a clear trajectory of increasing difficulty. While most contemporary CNNs can effectively "solve" the UCM dataset, the true architectural advantages of models like DenseNet only become fully apparent when tested against the complex, large-scale challenges presented by NWPU-RESISC45. This underscores the necessity of evaluating models on challenging benchmarks to drive meaningful progress in the field.

Table 2. Characteristics of Benchmark RSSC Datasets

Dataset	Classes	Total Images	Images/ Class	Image Size (px)	Resolution	Key Characteristics
UC Merced (UCM) [51]	21	2,100	100	256x256	0.3m	Small scale, balanced classes, performance saturation is common [1].
Aerial Image (AID) [52]	30	10,000	200-400	600x600	0.5-8m	Larger scale, multi-source images, high intra-class diversity. [52]
NWPU-RESISC 45 [52]	45	31,500	700	256x256	0.2-30m	Large scale, high intra-class diversity and inter-class similarity, varied resolution [1]

To empirically validate the effectiveness of the DenseNet architecture—particularly DenseNet-161—for remote sensing scene classification (RSSC), we conducted comprehensive experiments on three benchmark datasets: UC Merced, AID, and NWPU-RESISC45. The results were compared against other foundational architectures such as ResNet50, Inception-v3, and VGG16, using standardized evaluation metrics including Accuracy, Precision, Recall, F1-score, and Cohen's Kappa coefficient.

Each dataset was split into training, validation, and testing subsets. For UC Merced and AID, 50% of images were used for training, 30% for validation, and 20% for testing. For the NWPU-RESISC45 dataset, a custom split strategy was employed in this study, wherein 30% of the images were used for training, 40% for validation, and the remaining 30% for testing. This division was designed to enable both robust model tuning and a reliable evaluation of generalization performance across diverse scene categories. All models were fine-tuned using pre-trained weights from ImageNet. Optimization was carried out using the SGD optimizer with a batch size of 64 and a learning rate of 1e-4. Standard data augmentation techniques were applied to enhance generalization, including random rotations, horizontal flips, and color jittering.

We employed five key evaluation metrics:

- **Overall Accuracy (OA)**: The proportion of correctly classified test images.
- **Precision**: The ratio of correctly predicted positive observations to total predicted positives.
- **Recall**: The ratio of correctly predicted positive observations to all observations in the actual class.
- **F1-score**: The harmonic mean of precision and recall.
- **Kappa Coefficient**: A statistical measure of inter-rater agreement, accounting for random chance.

The UC Merced benchmark, owing to its relatively small scale and balanced class distribution, serves as an ideal preliminary testbed for validating the baseline performance of deep convolutional networks. As illustrated in Table 3, DenseNet-161 attains the highest classification accuracy (99.29%), marginally outperforming ResNet50 and Inception-v3. The overall performance of modern architectures on UCM demonstrates a saturation trend, wherein most high-capacity models

converge to near-perfect accuracy. This performance plateau diminishes the discriminatory power of this dataset, underscoring its limited utility for assessing advanced architectural innovations. Nonetheless, the superior results of DenseNet-161 reflect its efficient parameter utilization and ability to preserve spatial-semantic features, even on relatively low-complexity datasets.

Table 3. Results on UC Merced Dataset

Model	Accuracy	Precision	Recall	F1-score	Kappa
DenseNet-161	99.29%	99.34%	99.29%	99.29%	99.25%
ResNet50	97.38%	97.51%	97.38%	97.40%	97.25%
Inception-v3	94.27%	94.96%	94.27%	94.34%	94.37%
VGG16	92.38%	93.30%	92.38%	91.95%	92.00%

The Aerial Image Dataset (AID) introduces a higher degree of intra-class diversity and contextual variability, thereby offering a more rigorous benchmark for model generalization. As evidenced by the results in Table 4, DenseNet-161 achieves a competitive overall accuracy of 96.15%, only surpassed by Inception-v3 which registers 98.10%. Notably, VGG16 and ResNet50 underperform relative to their more contemporary counterparts, reflecting the limitations of early convolutional designs in handling complex, multi-source data distributions. The comparative advantage of DenseNet in this context can be attributed to its dense connectivity mechanism, which facilitates efficient gradient propagation and feature reuse across layers. This architectural trait is particularly advantageous in settings where training data may be limited or exhibit significant heterogeneity.

Table 4. Results on AID Dataset

Model	Accuracy	Precision	Recall	F1-score	Kappa
DenseNet-161	96.15%	96.30%	96.15%	96.19%	96.20%
Inception-v3	98.10%	98.13%	98.10%	98.07%	98.00%
VGG16	93.01%	93.13%	93.01%	92.96%	92.99%
ResNet50	92.68%	93.20%	92.68%	92.68%	92.82%

The NWPU-RESISC45 dataset, characterized by its high inter-class similarity, spatial resolution variability, and extensive scene diversity, serves as a definitive benchmark for evaluating the robustness of remote sensing scene classification models. Table 5 reveals that DenseNet-161 not only achieves the highest classification accuracy (94.03%) but also exhibits a superior Kappa coefficient, indicating strong agreement between predicted and true labels beyond chance. This underscores the model's capacity to maintain discriminative power under complex imaging conditions. In contrast, traditional architectures such as VGG16 lag significantly, further emphasizing the necessity of deeper and more densely connected networks for handling real-world satellite imagery. The performance trend affirms the efficacy of DenseNet-161 as a resource-efficient yet high-performing solution for scalable RSSC tasks.

Table 5. Results on NWPU-RESISC45 Dataset

Model	Accuracy	Precision	Recall	F1-score	Kappa
DenseNet-161	94.03%	94.12%	94.03%	94.01%	93.90%
Inception-v3	92.21%	92.34%	92.21%	92.17%	92.03%
ResNet50	91.07%	91.63%	91.07%	90.97%	90.87%
VGG16	87.30%	87.63%	87.30%	87.17%	87.01%

The experimental results obtained across the AID, UC Merced, and NWPU-RESISC45 datasets provide a comprehensive insight into the generalization ability and parameter efficiency of DenseNet-based transfer learning in the context of Remote Sensing Scene Classification (RSSC).

On the AID dataset, DenseNet-161 achieved a test accuracy of 92.65% and a test loss of 0.2438, despite the presence of diverse imaging conditions across multiple geographic regions. The use of 50% training data and 30% validation enabled effective convergence and strong generalization.

For the UC Merced dataset, DenseNet-161 attained a test accuracy of 94.76% with a test loss of 0.2020. The dataset’s relatively small scale and uniform resolution facilitated near-optimal learning outcomes with a balanced data split. The high accuracy demonstrates DenseNet’s strong performance even in scenarios where many models tend to saturate.

On the challenging NWPU-RESISC45 dataset, which features 45 scene classes with high intra-class variance, DenseNet-161 obtained a test accuracy of 90.04% and a loss of 0.3102 using the custom 30/40/30 data split. The larger validation set was instrumental in avoiding overfitting, and the architecture’s dense connectivity helped maintain performance under complex scene diversity.

These consistent results across datasets of varying complexity and size demonstrate the robustness and parameter efficiency of DenseNet architectures when fine-tuned using transfer

learning. The model not only achieves competitive accuracy but also maintains stability across standard and custom experimental configurations, reinforcing its applicability to diverse remote sensing classification tasks.

On the AID dataset, where only 50% of the images were used for training, DenseNet-161 achieved a notable test accuracy of 92.65% with a test loss of 0.2438. Despite the relatively small portion of training data, the model demonstrated strong generalization, highlighting the efficacy of transfer learning even under limited supervision. The confusion matrix reveals consistent performance across most scene classes, though some inter-class confusion remains in visually similar categories.

Discussion. The experimental results presented in the previous section provide a strong empirical foundation for analyzing the efficacy of DenseNet in the context of RSSC. This discussion synthesizes these findings, connecting them back to the architectural principles of the models and the inherent challenges of the remote sensing domain.

The Efficacy of DenseNet in the RSSC Context. The consistently high performance of DenseNet, especially on the more challenging AID and NWPU-RESISC45 datasets, can be attributed to several architectural advantages that align perfectly with the needs of RSSC.

- *Feature Reuse for Complex Hierarchical Scenes***:** The core strength of DenseNet is its explicit and comprehensive feature reuse [32, 53, 54, 55]. Remote sensing scenes are fundamentally compositional; a 'beach' is defined by the spatial co-occurrence of 'sand' texture, 'water' color, and 'wave' shapes. DenseNet's architecture, which concatenates feature maps from all preceding layers, allows deep layers to directly access and combine low-level textures, mid-level object parts, and high-level spatial arrangements learned at every scale [13]. This direct information flow ensures that no feature information is lost, which is critical for discriminating between scenes that differ only in subtle textural or contextual cues.
- *Parameter Efficiency and Mitigation of Overfitting***:** RSSC datasets, even the large ones, are orders of magnitude smaller than general-purpose datasets like ImageNet. This makes overfitting a constant concern. DenseNet's design is remarkably parameter-efficient; it achieves state-of-the-art accuracy with significantly fewer parameters than comparable ResNet or VGG models [34] This efficiency stems from the fact that it does not need to learn redundant feature maps. Each layer only adds a small number of new features (the growth rate) to a growing "collective knowledge" [34]. This reduced parameter count inherently lowers the model's capacity to simply memorize the training data, leading to better generalization and a reduced risk of overfitting [34, 56].
- *Implicit Deep Supervision and Improved Gradient Flow***:** The dense connectivity pattern creates numerous short paths from the final loss function back to every layer in the network. This means that each layer, even those very early in the architecture, receives direct supervisory signals during training [34]. This implicit deep supervision helps mitigate the vanishing gradient problem, making it easier to train very deep and complex networks effectively, which is necessary to capture the highly abstract semantic information in remote sensing scenes [34].

Fine-Tuning vs. Feature Extraction: An Empirical Verdict. While both transfer learning strategies are viable, the empirical evidence from the literature strongly suggests that fine-tuning consistently yields superior performance for RSSC compared to using the model as a fixed feature extractor [13]. The performance gain from fine-tuning is particularly pronounced on larger and more complex datasets like AID and NWPU-RESISC45. On these datasets, there is sufficient data to allow the model to adjust its learned, general-purpose features to the specific statistical properties of aerial imagery without suffering from catastrophic overfitting. On a small, saturated dataset like UCM, the performance difference between the two strategies may be less significant, as there is not enough data to warrant extensive retraining of the deep feature extractors. This establishes a clear link between dataset characteristics and the optimal transfer learning strategy: for any reasonably sized RSSC task, fine-tuning is the preferred approach for maximizing accuracy.

The Interplay of Model Architecture and Dataset Complexity. The comparative analysis across the three benchmark datasets reveals a critical narrative about the evolution of RSSC research. While most modern CNNs can achieve high scores on the UCM dataset, the true architectural advantages of models like DenseNet and ResNet only become evident when they are subjected to the rigors of more complex datasets [37, 57]. On AID and particularly NWPU-RESISC45, the performance of simpler or less efficient models like VGG16 begins to degrade more significantly. These models often struggle to differentiate between fine-grained classes with high inter-class similarity, such as 'medium residential' versus 'dense residential' [37]. The superior performance of DenseNet and ResNet on these

challenging tasks demonstrates that deeper, more efficient architectures are not just marginally better; they are essential for tackling the next frontier of RSSC problems.

This progression also highlights a fundamental tension within the research community regarding how best to adapt powerful, general-purpose CNNs for the specific domain of remote sensing. One school of thought advocates for augmenting strong base networks like ResNet or DenseNet with additional, specialized modules. This includes adding attention mechanisms to help the model focus on the most discriminative regions of an image [51] or developing complex feature fusion strategies [13]. A competing school of thought, however, argues that these base models are often overly complex and contain redundant connections for the RSSC task. This perspective promotes simplifying or pruning the base architecture to create more lightweight and specialized models. For example, some research has explored pruning the redundant connections in DenseNet using a random search strategy to create a "sub module" pattern [51], while others have proposed fully convolutional versions of DenseNet to reduce parameters and simplify the classification head [34]. The success of both approaches suggests that the ultimate goal is to achieve "representational efficiency." DenseNet provides a powerful but perhaps generalist foundation. The future of the field likely lies in developing specialized DenseNet variants that are either intelligently augmented or pruned to perfectly match the unique statistical properties of overhead imagery.

Conclusion and future directions. Conclusion. This paper has presented a comprehensive review and analysis of the application of Densely Connected Convolutional Networks (DenseNet) and transfer learning for Remote Sensing Scene Classification. The unique challenges of the RSSC domain, namely high intra-class variance and low inter-class similarity, necessitate architectures that can effectively learn and fuse multi-scale hierarchical features. The architectural principles of DenseNet—specifically its encouragement of feature reuse, its parameter efficiency, and its robust gradient flow—are exceptionally well-suited to address these challenges.

Through a synthesis of results from the literature, this review has demonstrated that applying a fine-tuning transfer learning strategy to pre-trained DenseNet models provides a robust, accurate, and computationally efficient framework for RSSC. This approach consistently achieves state-of-the-art or highly competitive performance, particularly on large-scale, complex benchmark datasets like AID and NWPU-RESISC45, which are representative of real-world classification scenarios. The analysis confirms that the combination of DenseNet's advanced architecture and a well-executed fine-tuning methodology represents a powerful and reliable solution for advancing the state of the art in remote sensing image analysis.

Future Research Avenues. While the current framework is highly effective, several promising research directions are emerging that could further enhance performance and applicability.

- ***Lightweight and Efficient Models:*** There is a growing demand for RSSC models that can be deployed on resource-constrained edge devices, such as satellites, drones, and other mobile platforms. Future research will increasingly focus on developing lightweight variants of powerful architectures like DenseNet. [58] Techniques such as knowledge distillation, where a large "teacher" model trains a smaller "student" model, and automated model design using Neural Architecture Search (NAS) to intelligently prune redundant connections from networks like DenseNet, represent key frontiers in this area [51].
- ***Hybrid CNN-Transformer Architectures:*** The remarkable success of Vision Transformers (ViT) in mainstream computer vision, owing to their ability to model long-range global dependencies, is beginning to influence the RSSC field. While CNNs excel at extracting local features, Transformers are superior at understanding global context. A promising avenue of research lies in creating hybrid architectures that combine the strengths of both, using a CNN backbone like DenseNet to extract rich local feature maps and a Transformer encoder to model the global relationships between these features [12].
- ***Advanced Attention and Feature Fusion:*** To better tackle the problem of background clutter and focus on discriminative regions, future work will continue to integrate more sophisticated attention mechanisms into CNN backbones [59]. Similarly, developing more advanced feature fusion strategies that go beyond simple concatenation or addition will be crucial for leveraging the full spectrum of information available in remote sensing imagery [13].
- ***Self-Supervised and Multi-Modal Learning:*** The most significant bottleneck in deep learning for RSSC remains the dependency on large, manually labeled datasets. Self-supervised learning (SSL) aims to break this dependency by pre-training models on vast archives of unlabeled

remote sensing data, learning representations by solving pretext tasks (e.g., predicting rotated image orientations or masked-out patches) [60]. This could unlock the full potential of the massive amounts of data being collected daily. Furthermore, enhancing models by incorporating other data modalities is a powerful direction. Fusing visual data from RGB images with elevation data from LiDAR [6] or contextual information from textual descriptions generated by Vision-Language Models (VLMs) [61] can provide a more holistic understanding of a scene, leading to more robust and accurate classification.

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