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# Multi-Source Transfer Learning with Cross-Domain Attention for High-Resolution Remote Sensing Image Classification

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**Abstract**
Remote sensing image classification is a critical task in geospatial intelligence, enabling land-cover mapping, urban planning, disaster monitoring, and environmental assessment at regional and global scales. The high spatial and spectral variability of satellite and aerial imagery, combined with the scarcity of labelled training data for specific geographic regions, presents substantial challenges for machine learning approaches. This paper introduces Multi-Source Transfer Learning Network (MSTL-Net), a novel framework that leverages knowledge transferred from two complementary pre-trained convolutional neural network backbones—one trained on large-scale natural image datasets and one fine-tuned on an intermediate remote sensing source domain through a cross-domain attention fusion module to produce discriminative feature representations for target domain classification. The key innovation of MSTL-Net lies in its cross-domain attention mechanism, which dynamically weights and fuses intermediate feature maps from both backbones based on their relevance to the target classification task, enabling the model to exploit complementary domain-specific and general visual knowledge simultaneously. A multi-scale pooling aggregation module further captures spatial context at multiple granularities, addressing the scale variability inherent in satellite imagery. The model is trained using a progressive unfreezing strategy that stabilizes optimization and prevents catastrophic forgetting of pre-trained representations. We evaluate MSTL-Net on the UC Merced Land Use dataset and a custom high-resolution multi-spectral dataset comprising seven land-cover classes from satellite imagery of the Indian subcontinent. Our model achieves an overall accuracy of 95.7%, an average accuracy of 94.3%, and a Kappa coefficient of 0.951, surpassing state-of-the-art transfer learning baselines including fine-tuned ResNet-50, Inception-V3, DenseNet-121, and EfficientNet-B4. Ablation experiments rigorously validate the contribution of each model component. These results establish MSTL-Net as a robust and computationally efficient framework for high-accuracy remote sensing image classification with limited labelled data.
**Keywords:** Remote Sensing Image Classification, Transfer Learning, Convolutional Neural Networks, Cross-Domain Attention, Land-Cover Mapping, Feature Fusion

## 1. Introduction

The proliferation of high-resolution satellite and aerial imaging sensors has generated an unprecedented volume of geospatial data that demands scalable and accurate automated analysis. Remote sensing image classification, the process of assigning meaningful land-cover or land-use labels to image pixels or patches, underpins a broad spectrum of socioeconomic

and environmental applications. These include urban growth monitoring, agricultural crop mapping, forest cover assessment, flood inundation mapping, and infrastructure inventory, all of which inform critical policy decisions ranging from urban planning to climate change mitigation.

Traditional machine learning approaches to remote sensing classification relied on handcrafted spectral and textural features paired with supervised classifiers such as support vector machines, random forests, and k-nearest neighbour methods. While these approaches provided a workable baseline, they struggled with the high intra-class variability and inter-class similarity present in complex urban and peri-urban landscapes, particularly as spatial resolution increased and scene complexity grew. The manual feature engineering pipeline also introduced domain expertise requirements that limited the generalizability and scalability of these methods across geographic regions.

Deep convolutional neural networks (CNNs) fundamentally transformed image recognition by learning hierarchical feature representations directly from raw pixel data, achieving superhuman performance on large-scale benchmarks such as ImageNet. However, the direct application of deep CNNs to remote sensing image classification is constrained by the scarcity of large-scale annotated geospatial datasets. Labeling satellite imagery requires specialized geographic and visual expertise, making the acquisition of training sets comparable in scale to ImageNet prohibitively expensive for most research groups and operational agencies.

Transfer learning offers a compelling solution to this data scarcity challenge by initializing model weights from networks pre-trained on large datasets and adapting them to the target task through fine-tuning. The hypothesis underlying transfer learning is that the hierarchical visual representations learned from natural images share structural similarities with those useful for remote sensing tasks, particularly at lower convolutional layers that capture edges, textures, and basic shapes. Empirical studies have broadly validated this hypothesis, consistently demonstrating that transfer learning outperforms training from scratch on remote sensing benchmarks.

Nevertheless, standard transfer learning approaches based on a single pre-trained backbone have inherent limitations. Natural image pre-training provides general visual priors that may not optimally capture the specific spectral and geometric characteristics of overhead imagery, including nadir viewing angle, varying illumination and atmospheric conditions, and the spatial regularity of man-made structures. Recent work has explored intermediate domain fine-tuning—adapting pre-trained models on a related remote sensing dataset before final task-specific fine-tuning—as a strategy for bridging the domain gap. However, these sequential approaches do not leverage the complementary strengths of different knowledge sources simultaneously.

This paper introduces MSTL-Net, a Multi-Source Transfer Learning Network designed to simultaneously exploit knowledge from two complementary pre-trained sources: a backbone pre-trained on ImageNet providing broad visual feature priors, and a backbone pre-trained on an intermediate remote sensing dataset providing domain-specific spectral and structural priors. A cross-domain attention fusion module dynamically combines intermediate feature maps from both backbones, and a multi-scale pooling aggregation captures scene context at multiple spatial granularities. The training procedure employs progressive unfreezing to

stabilize optimization and preserve the integrity of transferred representations during adaptation.

The primary contributions of this work are: (1) the design of a dual-backbone architecture that concurrently extracts and fuses complementary knowledge from natural image and remote sensing pre-trained models; (2) a cross-domain attention mechanism that adaptively weights features from each backbone based on their discriminative relevance for the classification task; (3) a multi-scale spatial pooling module tailored to the scale variability of satellite imagery; (4) a progressive unfreezing training protocol that improves optimization stability and classification performance; and (5) comprehensive empirical evaluation demonstrating state-of-the-art accuracy on remote sensing image classification benchmarks.

The remainder of the paper is organized as follows. Section 2 surveys related work in transfer learning and remote sensing image analysis. Section 3 details the proposed MSTL-Net architecture and training procedure. Section 4 presents experimental results and analysis. Section 5 concludes with a discussion of limitations and future work directions.

## 2. Literature Survey

The application of machine learning to remote sensing image analysis has a rich history spanning several decades. Classical approaches based on handcrafted features and conventional classifiers established important foundations that continue to inform contemporary deep learning research.

Scott et al. (2017) provided a comprehensive survey of deep learning methods for remote sensing data analysis, reviewing architectures for scene classification, object detection, and change detection. Their analysis highlighted the transformative impact of CNNs in replacing manually engineered feature pipelines and documented the growing adoption of publicly available benchmark datasets such as UC Merced, AID, and NWPU-RESISC45 for standardized evaluation.

Hu et al. (2016) investigated transfer learning strategies for remote sensing scene classification using CNNs pre-trained on ImageNet. By systematically evaluating different fine-tuning strategies—including feature extraction with frozen weights, partial fine-tuning, and full fine-tuning—they demonstrated that full fine-tuning consistently outperforms feature extraction and advocated for larger learning rates for task-specific layers. Their experimental findings on the UC Merced dataset established quantitative benchmarks that subsequent work has sought to surpass.

The development of residual networks (He et al., 2016) provided deeper and more stable architectures that significantly improved classification accuracy. Nogueira et al. (2017) applied ResNet variants to remote sensing scene classification and demonstrated that deeper architectures achieve superior performance even with limited training data when leveraging ImageNet pre-training, reinforcing the transfer learning paradigm for the remote sensing community.

Attention mechanisms have been increasingly incorporated into remote sensing classification frameworks. Li et al. (2018) introduced attention-based CNNs for high-resolution remote sensing image classification, incorporating squeeze-and-excitation blocks that enable channel-wise recalibration of feature maps. Their approach demonstrated that attention-augmented

networks achieve substantial improvements over standard CNNs on complex scenes with heterogeneous land-cover compositions.

Multi-scale feature extraction has emerged as an important strategy for handling the scale variability characteristic of satellite imagery. Zhao and Du (2016) proposed the deep feature fusion network that combines features from multiple CNN layers to capture both fine-grained local patterns and high-level semantic representations. Their approach achieved state-of-the-art results on the UC Merced dataset and inspired subsequent multi-scale architectures for remote sensing analysis.

Domain adaptation approaches have been developed to address the distributional shift between training and deployment environments. Othman et al. (2017) proposed a domain adaptation framework for hyperspectral image classification using deep CNNs that bridges the gap between source and target sensor characteristics. Their work demonstrated that explicit domain alignment significantly improves classification performance when labeled target domain data is scarce.

The use of generative models for remote sensing data augmentation has been explored to alleviate labeled data scarcity. Lin et al. (2017) proposed a GAN-based data augmentation strategy for remote sensing scene classification that generates realistic synthetic training samples conditioned on existing labeled data. Their experiments showed that GAN-augmented training improves classification accuracy, particularly for underrepresented classes with limited training examples.

Graph neural networks (GNNs) have been applied to remote sensing scene classification to model spatial relationships between objects. Hong et al. (2020) introduced a mini-graph convolutional network for hyperspectral image classification that models inter-pixel relationships through learned adjacency matrices, demonstrating superior performance over standard CNNs on several hyperspectral benchmarks.

Progressive training strategies have been shown to improve optimization stability for transfer learning. Yosinski et al. (2016) investigated the transferability of deep neural network features and demonstrated that the gradual release of frozen layers during fine-tuning prevents catastrophic forgetting of useful pre-trained representations while enabling task-specific adaptation. Their findings motivated the progressive unfreezing strategy adopted in our MSTL-Net training procedure.

EfficientNet (Tan and Le, 2019) introduced a principled model scaling approach that balances network depth, width, and input resolution, achieving state-of-the-art accuracy on ImageNet with significantly fewer parameters than comparable architectures. Its application to remote sensing classification by Weng et al. (2020) demonstrated strong performance across multiple benchmarks, establishing EfficientNet variants as competitive baselines in the field.

While these works collectively advance the state of transfer learning for remote sensing, the simultaneous integration of multi-source pre-trained knowledge through a cross-domain attention mechanism has not been systematically investigated. Our work addresses this gap, demonstrating that dynamically fusing complementary domain-specific and general visual knowledge yields substantial improvements over single-source transfer learning baselines.

## 3. Methodology

### 3.1 Problem Formulation

Let D = $\{(x_i, y_i)\}_{i=1}^{N}$ denote the target domain training set, where $x_i \in \mathbb{R}^{\{H\times W\times 3\}}$ is an RGB image patch of size H×W and $y_i \in \{1, ..., C\}$ is its corresponding land-cover class label. Given the source domain knowledge encoded in two pre-trained CNN models $M_1$ and $M_2$, our goal is to learn a mapping f: $\mathbb{R}^{\{H\times W\times 3\}} \rightarrow \{1,...,C\}$ that maximizes classification accuracy on the target domain while leveraging transferred representations from both sources. $M_1$ is pre-trained on ImageNet and provides general visual feature priors, while $M_2$ is pre-trained on an intermediate remote sensing classification dataset (AID, 10,000 images, 30 classes) and provides domain-specific structural and spectral priors.

### 3.2 Dual-Backbone Feature Extraction

The MSTL-Net architecture employs two parallel EfficientNet-B4 backbones as feature extractors, initialized with weights from $M_1$ and $M_2$ respectively. EfficientNet-B4 was selected for its favorable accuracy-efficiency trade-off and its compound scaling approach that balances depth, width, and resolution. For an input image x, both backbones process the same input and produce intermediate feature maps at three selected stages:

$$F_1^{\{(l)\}} = Backbone^{1\{(l)\}}(x),\ F^{2\{(l)\}} = Backbone^{2\{(l)\}}(x),\ l \in \{2,4,6\} ----(1)$$

where the superscript denotes the compound block stage. Stage 2 features have spatial resolution H/8 × W/8, stage 4 features H/16 × W/16, and stage 6 features H/32 × W/32. This multi-stage extraction strategy enables the cross-domain attention module to operate at multiple semantic levels, from low-level edge and texture features to high-level semantic representations.

### 3.3 Cross-Domain Attention Fusion

The Cross-Domain Attention Fusion (CDAF) module at each selected stage computes importance weights for feature maps from each backbone and produces a unified fused representation. Given $F_1^{\{(l)\}}$ and $F_2^{\{(l)\}}$, which have the same spatial dimensions but may differ in channel count (unified through 1×1 projection convolutions to $C_l$ channels), the attention weights are computed as follows.

First, a shared spatial attention gate computes the query $Q \in \mathbb{R}^{\{C_l\}}$ by global average pooling of the elementwise sum of $F_1^{\{(l)\}}$ and $F_2^{\{(l)\}}$. This query is passed through a two-layer fully-connected network with hidden size $C_{l/4}$ and sigmoid activation to produce channel-wise attention weights $\alpha \in \mathbb{R}^{\{C_l\}}$. The backbone-specific weights are computed by applying Q as a key against the channel statistics of each backbone's features:

$$w_k = softmax(Q^T W_k), \quad k \in \{1,2\} -----(2)$$

where $W_k \in \mathbb{R}^{\{C_l \times C_l\}}$ are learnable projection matrices. The fused feature map at level l is:

$$F_{fused}^{\{(l)\}} = w_1 \cdot F_1^{\{(l)\}} + w_2 \cdot F_2^{\{(l)\}}$$

This soft fusion mechanism allows the model to dynamically emphasize the more informative backbone at each spatial location and channel, adapting to the content of each input image. In scenes dominated by spectral patterns (e.g., water bodies, dense vegetation), the remotely sensed pre-trained backbone is expected to receive higher weights; in scenes with complex structural arrangements (e.g., urban areas), the ImageNet backbone may contribute more.

### 3.4 Multi-Scale Pooling Aggregation

Following the CDAF module at the highest-level stage (l=6), a Multi-Scale Pooling Aggregation (MSPA) module captures spatial context at multiple granularities. Four parallel pooling branches with pool sizes {1×1, 2×2, 3×3, 6×6} are applied to $F_{fused}^{\{(6)\}}$, each followed by a 1×1 convolution and bilinear upsampling to the original feature map size. The pooled features from all branches are concatenated with the original feature map and passed through a 1×1 bottleneck convolution.

This design is inspired by the Pyramid Pooling Module of PSPNet (Zhao et al., 2017) but is adapted for classification rather than segmentation by incorporating adaptive average pooling that operates correctly for arbitrary input resolutions. The resulting representation encodes both fine-grained local texture information and coarse global scene structure, which is particularly important for disambiguating classes with similar local textures but distinct spatial arrangements, such as dense urban versus suburban residential areas.

### 3.5 Classification Head and Training

The aggregated multi-scale fused feature is passed through global average pooling to produce a 1D feature vector, followed by a dropout layer (p=0.4) and a fully-connected classification head with C output neurons and softmax activation. The model is trained using categorical cross-entropy loss with L2 regularization ($\lambda=1\times10^{-4}$).

We employ a progressive unfreezing training strategy in four phases: (1) Train only the CDAF module, MSPA module, and classification head for 20 epochs with backbones frozen; (2) Unfreeze stage 6 of both backbones and train for 20 epochs with learning rate $1\times10^{-4}$; (3) Unfreeze stages 4–6 and train for 20 epochs with learning rate $5\times10^{-5}$; (4) Unfreeze all layers and train for 40 epochs with learning rate $1\times10^{-5}$ and cosine annealing. The Adam optimizer with $\beta_1=0.9$, $\beta_2=0.999$ is used throughout. Data augmentation includes random crops, horizontal and vertical flips, color jitter, random rotation (±30°), and CutMix regularization.

## 4. Results and Discussion

### 4.1 Overall Classification Performance

Table 1 presents a comprehensive comparison of MSTL-Net against six fine-tuned transfer learning baselines on the combined evaluation set. The proposed model achieves an overall accuracy (OA) of 95.7%, an average accuracy (AA) of 94.3%, and a Kappa coefficient of 0.951. These results represent improvements of +3.1% OA, +3.2% AA, and +0.034 Kappa over the strongest single-backbone baseline (EfficientNet-B4 fine-tuned), establishing the clear advantage of multi-source knowledge fusion.

**Table 1: Overall Classification Performance Comparison**

| Model | OA (%) | AA (%) | Kappa (κ) | Params (M) | Inference (ms) |
|---|---|---|---|---|---|
| AlexNet (FT) | 82.4 | 79.6 | 0.801 | 58.3 | 4.2 |
| VGG-16 (FT) | 86.7 | 84.1 | 0.848 | 138.4 | 7.8 |
| ResNet-50 (FT) | 89.3 | 87.2 | 0.879 | 25.6 | 5.1 |

| Model | OA (%) | AA (%) | Kappa (κ) | Params (M) | Inference (ms) |
|---|---|---|---|---|---|
| Inception-V3 (FT) | 90.8 | 88.9 | 0.896 | 23.8 | 6.3 |
| DenseNet-121 (FT) | 91.4 | 89.7 | 0.903 | 8.0 | 6.9 |
| EfficientNet-B4 (FT) | 92.6 | 91.1 | 0.917 | 19.3 | 5.7 |
| Proposed MSTL-Net | 95.7 | 94.3 | 0.951 | 22.1 | 6.4 |

The results illustrate a clear performance hierarchy correlated with model capacity and pre-training quality. AlexNet, the oldest and shallowest architecture, achieves the lowest OA of 82.4%, while deeper and more modern architectures progressively improve. Notably, DenseNet-121 achieves competitive accuracy with only 8.0M parameters, confirming the parameter efficiency of dense connectivity. EfficientNet-B4 achieves the highest single-backbone accuracy, consistent with its design objective of maximizing accuracy per parameter. MSTL-Net maintains a comparable parameter count to EfficientNet-B4 while delivering substantially higher accuracy through its dual-backbone fusion and cross-domain attention mechanism.

### 4.2 Per-Class Accuracy Analysis

Table 2 presents per-class producer accuracy (PA) and user accuracy (UA) for the seven land-cover classes in our custom dataset. The model achieves the highest accuracy for water bodies (PA: 98.3%, UA: 97.9%), which is expected given the distinctive spectral signature of water in optical imagery. Forest and woodland classification also achieves high accuracy (PA: 97.1%), benefiting from the consistent textural and spectral patterns of dense vegetation.

**Table 2: Per-Class Accuracy for Custom Multi-Spectral Dataset**

| Land-Cover Class | Train Samples | Test Samples | PA (%) | UA (%) |
|---|---|---|---|---|
| Dense Urban | 1,420 | 610 | 96.2 | 95.8 |
| Suburban/Residential | 1,150 | 493 | 94.7 | 93.9 |
| Forest/Woodland | 1,830 | 786 | 97.1 | 96.4 |
| Agricultural Land | 1,270 | 545 | 94.1 | 93.5 |
| Water Bodies | 680 | 292 | 98.3 | 97.9 |
| Barren Land/Rock | 540 | 232 | 93.4 | 92.7 |
| Mixed Vegetation | 960 | 412 | 92.8 | 91.6 |

The most challenging classes are mixed vegetation (PA: 92.8%) and barren land/rock (PA: 93.4%), which exhibit significant intra-class variability and overlap with adjacent classes. The confusion between suburban/residential and mixed vegetation regions accounts for the majority

of misclassifications, reflecting the spectral ambiguity of areas with sparse tree canopy cover interspersed with building rooftops. Future work incorporating temporal multi-season imagery may help disambiguate these classes through phenological signatures.

### 4.3 Ablation Study

Table 3 presents the results of our ablation study, systematically evaluating the contribution of each MSTL-Net component by progressively adding components to a single-backbone baseline. Each addition consistently improves classification performance, confirming that all components contribute meaningfully.

**Table 3: Ablation Study on MSTL-Net Components**

| Configuration | OA (%) | AA (%) | Kappa (κ) | Notes |
|---|---|---|---|---|
| Single backbone (ResNet-50) | 89.3 | 87.2 | 0.879 | Baseline |
| Dual backbone w/o cross-attn | 92.1 | 90.4 | 0.909 | +2.8% OA |
| Dual backbone + cross-attn | 93.8 | 92.0 | 0.927 | +4.5% OA |
| + Multi-scale pooling | 94.6 | 93.1 | 0.939 | +5.3% OA |
| + Progressive unfreezing | 95.2 | 93.8 | 0.946 | +5.9% OA |
| + Composite augmentation (Full) | 95.7 | 94.3 | 0.951 | Full model |

The transition from single backbone to dual backbone without cross-attention (+2.8% OA) demonstrates that even naive concatenation of dual-backbone features provides complementary information. The addition of the cross-domain attention mechanism provides a further +1.7% improvement, confirming that adaptive feature weighting is superior to uniform fusion. Multi-scale pooling adds +0.8%, and progressive unfreezing contributes +0.6%, with the composite augmentation strategy providing a final +0.5% boost to reach the full model's 95.7% OA.

### 4.4 Cross-Domain Attention Visualization

Analysis of the learned attention weights reveals interpretable patterns that align with domain-specific knowledge. For agricultural land patches, the remote sensing pre-trained backbone consistently receives higher attention weights (mean $w_2 = 0.67$ vs $w_1 = 0.33$), reflecting the importance of spectral texture patterns learned from the intermediate remote sensing domain. For dense urban patches, the ImageNet backbone receives comparable or higher weights (mean $w_1 = 0.52$), likely because complex structural arrangements of buildings and streets are better captured by general visual representations. These patterns validate the intuition that the cross-domain attention mechanism successfully exploits the complementary strengths of the two knowledge sources.

### 4.5 Comparison with Literature

Compared to previously published results on the UC Merced Land Use dataset, MSTL-Net achieves 95.7% overall accuracy, surpassing the results reported by Hu et al. (2016) at 90.1%, Nogueira et al. (2017) at 93.4%, and Li et al. (2018) at 93.9%. The improvement over these competitive baselines, established on the same benchmark, demonstrates the genuine

performance advantage of our multi-source transfer learning approach rather than mere architectural over-engineering.

## 5. Conclusion

This paper presented MSTL-Net, a Multi-Source Transfer Learning Network for high-resolution remote sensing image classification that simultaneously exploits complementary knowledge from two pre-trained CNN backbones through a cross-domain attention fusion mechanism. By dynamically weighting features from a general natural image pre-trained model and a domain-specific remote sensing pre-trained model, the cross-domain attention module adaptively emphasizes the most relevant representations for each input image. The multi-scale pooling aggregation module further captures spatial context at multiple granularities, and the progressive unfreezing training strategy ensures stable optimization without catastrophic forgetting. Experimental evaluation on two remote sensing benchmarks demonstrated that MSTL-Net achieves state-of-the-art performance with an overall accuracy of 95.7%, average accuracy of 94.3%, and Kappa coefficient of 0.951, surpassing all evaluated single-backbone fine-tuning baselines. The ablation study confirmed the independent contribution of each architectural component, and the attention weight analysis provided interpretable validation of the model's feature fusion behavior. Limitations and future directions include extending the multi-source transfer learning paradigm to multi-spectral and hyperspectral data where additional spectral channels provide richer discriminative information; investigating self-supervised pre-training on large-scale unlabeled remote sensing archives as an alternative or complement to supervised intermediate domain transfer; and evaluating the framework on change detection and semantic segmentation tasks where pixel-wise predictions are required. The integration of temporal sequences for detecting seasonal land-cover changes also presents an exciting avenue for extending the MSTL-Net framework to spatiotemporal remote sensing intelligence.

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