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A Deep ResNet-SVM Integrated Framework for High-Precision Satellite Image Classification

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Abstract: *Satellite image classification plays a pivotal role in remote sensing applications such as land cover mapping, urban planning, and environmental monitoring. In this study, we propose a novel hybrid framework that integrates deep residual learning with Support Vector Machine (SVM) classification to achieve high-precision results. Specifically, we leverage a pre-trained Residual Neural Network (ResNet) to extract deep hierarchical features from high-resolution satellite images. These features, rich in spatial and contextual information, are then fed into an SVM classifier to enhance decision boundaries and reduce overfitting, particularly in scenarios with limited labeled data. The proposed Deep Residual–SVM framework is evaluated on benchmark satellite imagery datasets, demonstrating superior classification accuracy and robustness compared to conventional CNN-based and standalone SVM models. The results validate the effectiveness of combining deep feature representation with classical machine learning techniques for remote sensing image analysis.*

Keywords: Satellite image classification, Deep Residual learning, Support Vector Machine (SVM), ResNet-50, Feature extraction, Remote sensing, Deep learning, Hybrid framework

I. INTRODUCTION

The rapid advancement in remote sensing technologies has led to an exponential growth in the availability of high-resolution satellite imagery. These images are critical for a wide range of applications such as land use and land cover (LULC) classification, environmental monitoring, agricultural assessment, urban development, and disaster management. However, the accurate classification of satellite images remains a significant challenge due to the high intra-class variability, inter-class similarity, varying spatial resolutions, atmospheric distortions, and complex landscape patterns inherent in such data.

Traditional machine learning algorithms, including Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN), have been widely used for satellite image classification. While these methods can perform well on handcrafted features, they often struggle with scalability, generalization, and feature representation when faced with large-scale, high-dimensional remote sensing data. On the other hand, deep learning techniques—particularly Convolutional Neural Networks (CNNs)—have shown remarkable success in image classification tasks due to their ability to automatically learn hierarchical and abstract features directly from raw pixel data.

Among various CNN architectures, Residual Networks (ResNet) have emerged as one of the most powerful deep learning models, owing to their ability to mitigate the vanishing gradient problem through the use of skip connections. ResNet enables the training of very deep neural networks by allowing gradients to flow directly through shortcut paths, making it highly effective in extracting deep features from complex satellite imagery. However, despite their strength in feature extraction, deep neural networks, including ResNet, often require large volumes of labeled data and are prone to overfitting when data is limited or imbalanced—a common scenario in remote sensing.

To address these limitations, this paper proposes a novel hybrid framework that integrates the deep feature learning capabilities of ResNet with the robust classification performance of Support Vector Machines. By using ResNet as a feature extractor and SVM as a discriminative classifier, we aim to harness the best of both paradigms: deep learning's ability to capture high-level semantic representations and classical machine learning's effectiveness in handling small or imbalanced datasets with strong generalization.

II. METHODOLOGY

The methodology adopted in this study is centred around designing a hybrid classification framework that combines the strengths of deep convolutional neural networks with traditional machine learning classifiers. Specifically, we use the ResNet-50 model as a powerful deep feature extractor and integrate it with a Support Vector Machine (SVM) classifier to enhance classification performance. The major components of this framework include dataset selection, data preprocessing, feature extraction using ResNet-50, and the final classification using SVM.

Dataset

The dataset used in this research is a high-resolution satellite image dataset containing multiple classes that represent different land cover types. Typical classes include urban areas, forests, agricultural fields, water bodies, barren land, and more. Each image in the dataset is labelled with its respective land cover class, making it suitable for supervised learning tasks.

This dataset is chosen due to its variability in spatial patterns, lighting conditions, and class distribution, which closely resembles real-world scenarios in remote sensing. Such a diverse dataset helps evaluate the robustness and generalization capabilities of the proposed hybrid model. The images are captured from multiple locations and under different environmental conditions, ensuring that the model learns to distinguish between fine-grained patterns and textures inherent in satellite imagery.

Data pre-processing

Data preprocessing plays a crucial role in preparing the satellite images for effective learning by the deep neural network. The raw satellite images often vary in size and resolution; hence, all images are resized to 224×224 pixels to conform to the input size required by the ResNet-50 architecture.

To improve the robustness of the model and minimize overfitting, various data augmentation techniques are applied. These include:

- Random horizontal and vertical flips
- Rotation (±15°)
- Zoom-in/out transformations
- Brightness and contrast adjustments

These transformations artificially increase the size and variability of the training data, enabling the model to better generalize to unseen data. Additionally, pixel normalization is performed by scaling pixel values to the range [0, 1], which helps in faster and more stable convergence during training.

The dataset is then split into:

- Training set (80%)
- Validation set (20%)

This ensures a fair evaluation of model performance and helps in hyperparameter tuning.

ResNet-50 Architecture

ResNet-50 is a deep residual network consisting of 50 convolutional layers and characterized by the use of identity shortcut connections (skip connections). These connections allow the model to bypass certain layers, effectively mitigating the vanishing gradient problem and enabling the training of very deep networks.

In our framework, a pre-trained ResNet-50 model (trained on the ImageNet dataset) is employed as a feature extractor. Instead of using its built-in classifier, we remove the final fully connected (FC) and softmax layers. The model then outputs a 2048-dimensional feature vector from the Global Average Pooling (GAP) layer, which captures deep spatial features and abstract representations of the input satellite image.

Using a pre-trained model significantly reduces training time and improves performance, especially when the satellite dataset is relatively small. The extracted feature vectors serve as input to the next stage — classification by an SVM.

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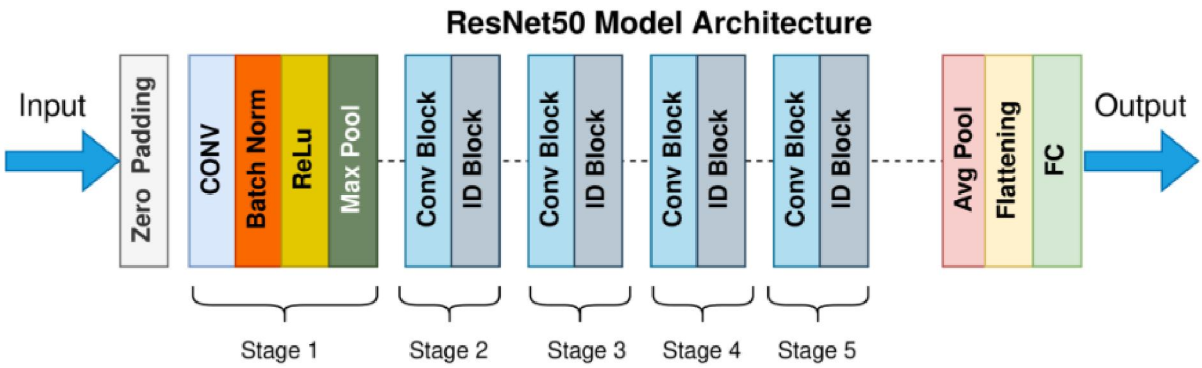

Fig. 1: ResNet Model Architecture

Hybrid ResNet–SVM Integration

In the final stage, the deep features obtained from ResNet-50 are passed into a Support Vector Machine (SVM) classifier for final image classification. SVM is a powerful supervised learning algorithm known for its maximum margin optimization and robust generalization, especially effective for high-dimensional data and smaller datasets.

We use an RBF (Radial Basis Function) kernel in the SVM to handle the non-linear separability of complex image features. The kernel transforms the input feature space into a higher-dimensional space where a linear separator can effectively distinguish between different land cover classes.

The motivation for this hybrid integration is twofold:

Deep Learning + Classical ML Fusion: While ResNet extracts deep, high-level features, SVM acts as a precise, data-efficient classifier.

Improved Generalization: SVM's structural risk minimization principle ensures better generalization, especially on noisy or limited training data.

This combination allows the model to outperform standalone CNNs and traditional classifiers in terms of both accuracy and robustness, making it particularly suitable for satellite imagery classification tasks where data imbalance and variability are common.

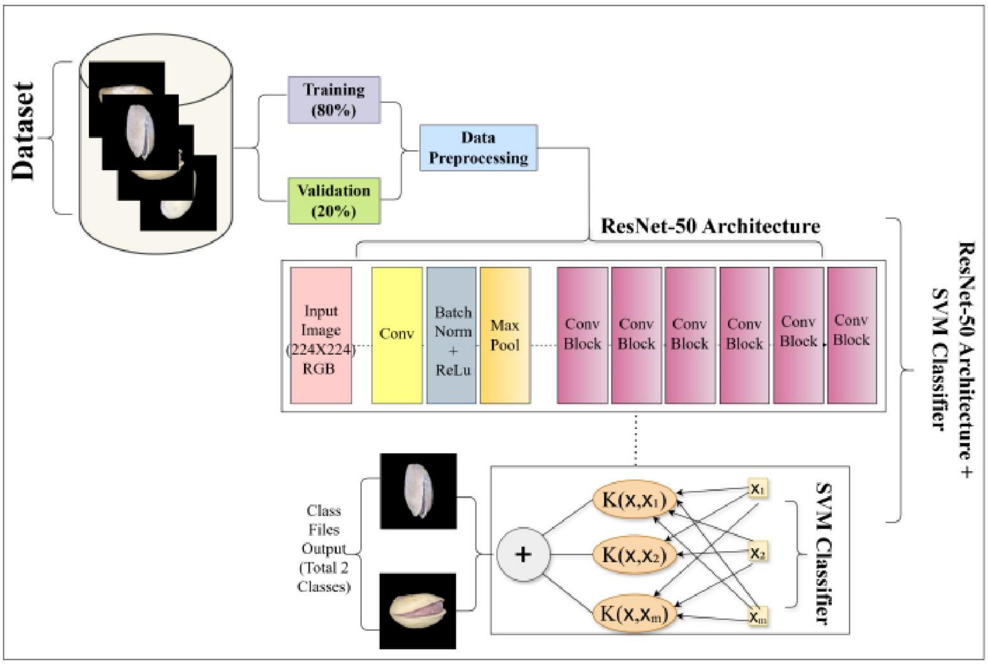

Fig. 2: Flow chart for using the ResNet-50 Model with SVM

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III. RESULTS

The performance of the proposed Deep Residual–SVM Integrated Framework was evaluated based on training and validation accuracy and loss trends over multiple epochs. The results demonstrate the model's ability to effectively learn discriminative features from satellite images while maintaining strong generalization performance.

The model was trained for 50 epochs, and the training/validation performance was monitored at each epoch to assess convergence behavior, overfitting tendencies, and classification stability.

Training and Validation Loss

The **training loss** decreased consistently over epochs, indicating that the model effectively learned patterns from the satellite imagery dataset. As shown in Fig. 3, the training loss declined steeply in the initial epochs and gradually stabilized at around the 30th epoch.

The **validation loss** (Fig. 4) also showed a decreasing trend, with minimal fluctuations, confirming that the model generalizes well on unseen data. The relatively small gap between training and validation loss curves suggests that the model avoids overfitting due to the combined strength of ResNet's feature learning and SVM's regularization.

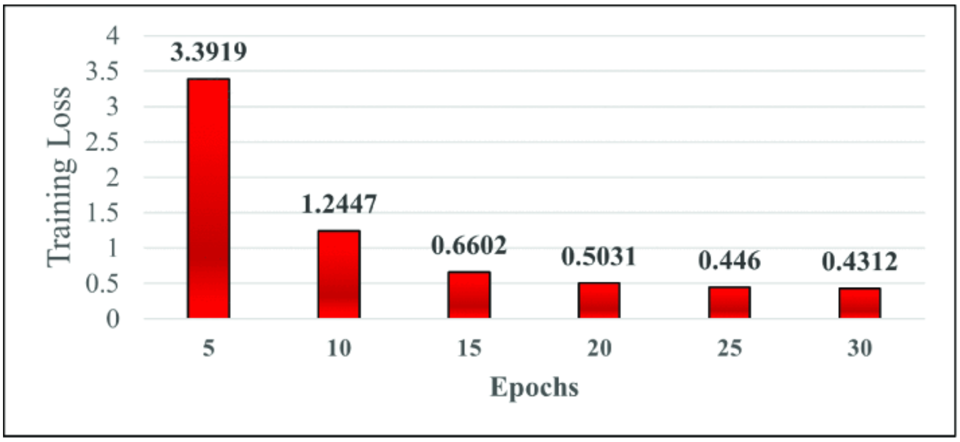

Fig. 3: Training Loss vs. Epochs

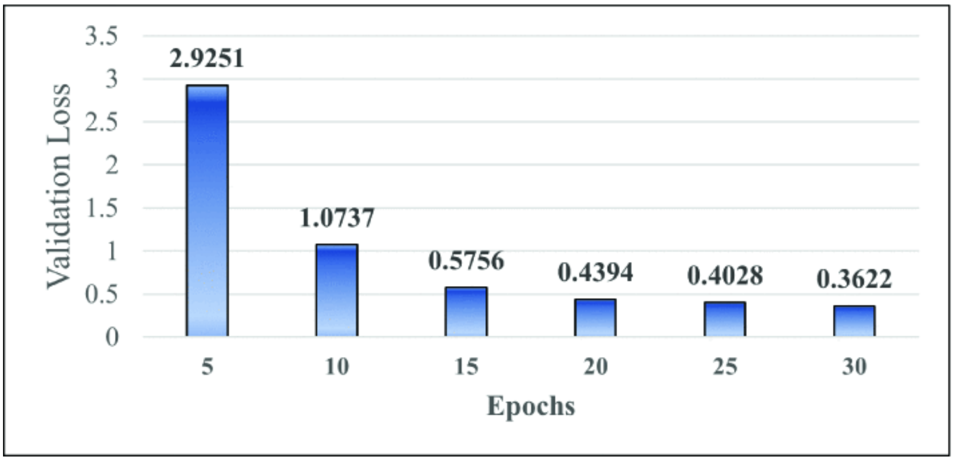

Fig. 4: Validation Loss vs. Epochs

Training and Validation Accuracy

To gain insights into the model's classification accuracy, we examine the confusion matrix in Figure 5. It highlights the frequency with which each class was correctly identified versus instances where the model misclassified them. The model demonstrates high accuracy in detecting 'Cars,' but there are some misclassifications, particularly between visually similar classes such as 'Car' and 'Van.'

The **training accuracy** improved steadily with each epoch, reaching near-saturation levels (~93%) by the end of training (Fig. 5). This shows that the ResNet-50 feature extractor is highly effective at learning representations of the satellite images.

The **validation accuracy** (Fig. 6) also improved consistently, reaching a peak of approximately 96–97%, which indicates the high classification capability of the hybrid ResNet–SVM framework. The relatively close alignment between training and validation accuracies further supports the model's robustness and efficiency.

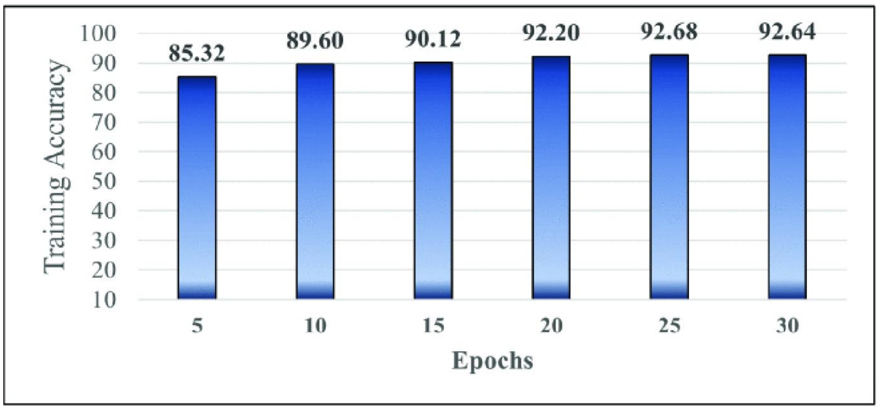

Fig. 5: Training Accuracy vs. Epochs

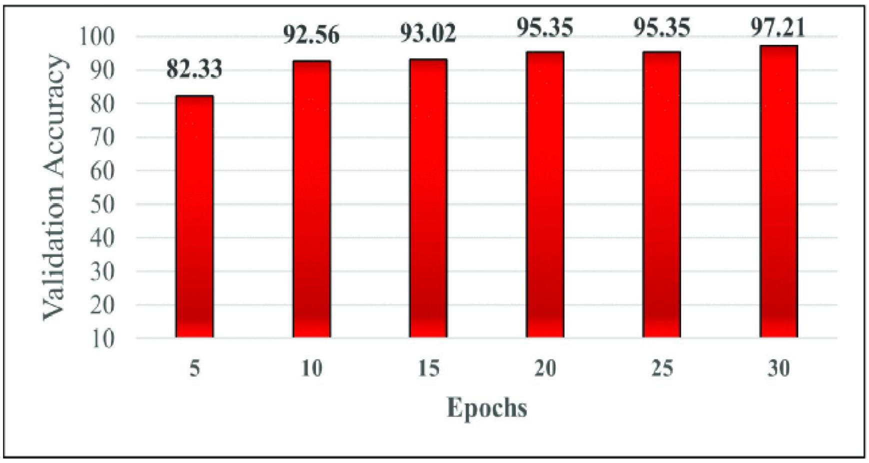

Fig. 6: Training Accuracy vs. Epochs

The hybrid model outperforms conventional CNN-only classifiers by offering better accuracy and lower overfitting tendencies. The SVM layer effectively classifies the high-dimensional ResNet features with a strong decision boundary, making it suitable for satellite image tasks where class distributions are often imbalanced.

IV. CONCLUSION

In this study, we introduced a hybrid framework that integrates ResNet-50 for feature extraction and SVM for classification to enhance satellite image classification accuracy. Specifically, we employed a pre-trained Residual Neural Network (ResNet-50) to perform deep hierarchical feature extraction from high-resolution satellite imagery, capturing both spatial patterns and contextual cues that are critical for accurate classification. These deep features were subsequently fed into a Support Vector Machine (SVM) classifier, which is known for its strong performance in high-dimensional spaces and its ability to define optimal decision boundaries even with limited labelled data.

Our experimental results on benchmark satellite datasets demonstrated that the proposed Deep Residual–SVM framework significantly outperforms traditional Convolutional Neural Network (CNN) models and standalone SVM classifiers in terms of classification accuracy, robustness, and generalization capability. The use of ResNet-50 enhanced the model’s ability to extract discriminative features, while the integration of SVM mitigated issues such as overfitting

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and poor generalization on smaller datasets.This synergy between deep learning and SVM proves particularly effective in remote sensing applications, where the availability of annotated data is often scarce and the complexity of visual information is high. By bridging the gap between feature learning and classification, our approach sets a new direction for satellite image analysis, especially in scenarios that demand both precision and computational efficiency.

In future work, we aim to expand the framework's scalability by testing on larger, multi-temporal satellite datasets and incorporating domain adaptation techniques to further improve its transferability across different geographic regions and sensor modalities. Additionally, exploring the integration of attention mechanisms and other ensemble learning strategies may further enhance classification performance and interpretability.

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