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CLASSIFYING THE PHASES OF SATELLITE IMAGE DETECTION WITH RESNET

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Abstract:
Satellite imaging is essential for environmental monitoring, urban planning, agriculture, and disaster management. This study explores using the ResNet152v2 convolutional neural network to classify satellite images into water bodies, cloudy areas, greenery, and deserts. ResNet152v2, known for its image recognition capabilities, is trained on a diverse dataset to ensure robust performance. Preprocessing techniques like normalization and augmentation enhance model performance. The ResNet152v2 model achieves high accuracy, particularly in identifying water bodies and greenery, though cloudy areas and deserts pose more challenges. This deep learning approach improves both the efficiency and accuracy of satellite image classification, advancing remote sensing and automated geospatial data analysis.

Keywords — **ResNet152v2, Satellite Image Classification, Deep Learning, Image Preprocessing, Python**

I. INTRODUCTION

Satellite imaging has greatly improved our ability to monitor and analyze the Earth's surface, essential for environmental monitoring, urban planning, agriculture, and disaster management. However, the increasing volume of satellite data requires advanced analysis techniques. Traditional methods, often manual or basic, are time-consuming and error-prone.

Deep learning, particularly convolutional neural networks (CNNs), offers new opportunities for automating and enhancing image classification. ResNet, a leading architecture in this field, excels in automatic feature extraction and image recognition, making it ideal for satellite image classification.

This research aims to develop an automated system using ResNet to classify satellite images into categories like water bodies, cloudy areas, greenery, and deserts. The process involves training the model on labeled images and evaluating its performance with standard metrics. By improving classification accuracy and efficiency, this study contributes to remote sensing and supports better decision-making in environmental and resource management.

The framework includes data acquisition from sources like NASA, preprocessing to enhance image quality, and techniques for image segmentation and feature extraction. Change detection is addressed through various methodologies, including pixel-based and object-based approaches, with machine learning models enhancing accuracy.

Tools such as ENVI, QGIS, Python, and TensorFlow are used, though challenges like data quality, variability, and the need for reliable labeled datasets remain. This methodology provides a comprehensive guide for satellite image analysis, offering insights into land cover categorization and change detection for researchers and practitioners.

II. EXISTING SYSTEM

The current system aims to address the identified issues by introducing an advanced solution for satellite image difference and change detection. This new system is designed to provide timely, accurate, and actionable information critical for urban planning, environmental conservation, and disaster management. It employs advanced techniques to ensure precise image registration, achieving pixel-to-pixel correspondence across different time periods. The system also utilizes cutting-edge machine learning algorithms, such as Convolutional Neural Networks (CNNs) and deep learning models, to detect land cover differences effectively. To ensure the accuracy and reliability of the change detection results, robust validation techniques, including the use of ground truth data and cross-validation, are employed. By integrating state-of-the-art technologies and methodologies, the proposed system offers a comprehensive solution for monitoring and managing environmental and urban changes. It aims to equip decision-makers with the necessary tools and information to make informed decisions regarding land use, conservation efforts, and disaster preparedness.

Satellite images often suffer from low brightness levels, which underscores the importance of image enhancement while preserving essential details without losing information. Contrast is a key parameter in subjectively evaluating an image's quality, as it distinguishes objects from the background based on color and brightness differences. Numerous algorithms have been developed to enhance contrast and address various brightness-related challenges in image processing. Contrast enhancement is also a critical preliminary step before applying other image processing techniques, such as segmentation and object identification.

Image enhancement techniques are generally categorized into spatial and frequency domain methods. Histogram Equalization (HE) is one of the most widely used image enhancement methods, applicable to the entire image or specific parts of it, and can significantly improve overall image quality. However, HE has limitations, such as its inability to retain the average intensity in an image. To overcome this, several modified versions of HE have been developed, including Bi-Histogram Equalization (BHE) and Recursive Mean Separate HE (RMSHE). shorten this content.

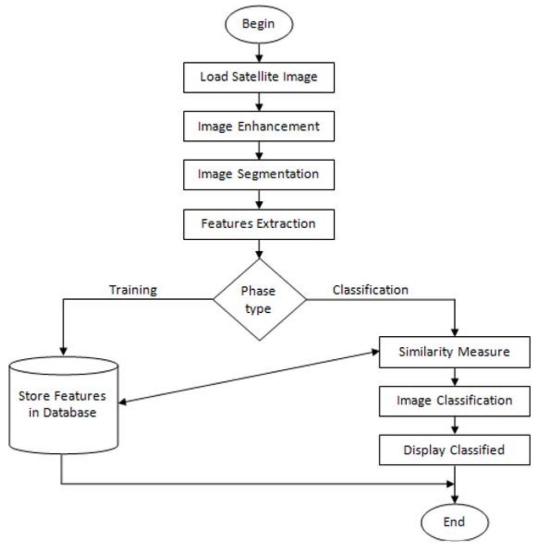

Fig. 1Architecture Diagram of Existing System

III. PROPOSED SYSTEM

The proposed methodology begins with acquiring satellite images from reputable sources, followed by preprocessing steps to improve image quality. The ResNet deep learning model will then be trained on labeled datasets to classify images into categories such as water bodies, cloudy areas, greenery, and deserts. To aid in land cover classification, image segmentation and feature extraction techniques will be employed. The model's performance will be thoroughly evaluated using standard metrics to ensure both accuracy and efficiency. This approach aims to enhance satellite image classification, thereby supporting informed decision-making in environmental management.

ResNet-152 v2 is a deep convolutional neural network with 152 layers, known for its outstanding performance in satellite image classification. It leverages residual connections to facilitate the training of very deep models, making it highly effective in distinguishing features such as water bodies, clouds, and greenery.

The preprocessing steps involve resizing images, normalization, and data augmentation to enhance the model's performance. The architecture comprises convolutional layers with batch normalization and ReLU activation, organized into residual blocks. The model is trained using cross-entropy loss and optimized with the Adam optimizer. Evaluation metrics include accuracy, precision, recall, and F1-score. This architecture is particularly well-suited for remote sensing applications, especially in environmental monitoring.

A. Input Layer

The input layer of ResNet152v2 requires fixed-size 200x200 pixel RGB images. Prior to inputting the images into the network, they are resized and normalized. Additionally, data augmentation techniques such as random cropping and flipping may be applied to standardize the data and improve the model's generalization capabilities.

B. Convolutional Layer

The first layer of ResNet utilizes a 7x7 convolutional kernel with a stride of 2 to perform initial feature extraction, capturing fundamental features from the image. This layer includes batch normalization to stabilize learning and accelerate training, followed by a ReLU activation function to introduce non-linearity, allowing the network to learn more complex patterns.

C. Residual Blocks

ResNet utilizes residual blocks, which are divided into identity blocks (for unchanged dimensions) and convolutional blocks (for varying dimensions). These blocks feature skip connections that allow the input to bypass certain layers and be added directly to the output. As images pass through these blocks, the network progressively extracts more abstract features, starting from simple edges and advancing to intricate patterns.

D. Pooling Layer

During training, a loss function such as categorical cross-entropy calculates the discrepancy between the predicted and actual class labels. Optimization algorithms like SGD or Adam then adjust the network's parameters to reduce this loss. This iterative process, carried out over numerous epochs, enhances the model’s classification accuracy.

E. Model Regularization Techniques

To avoid overfitting, dropout layers randomly deactivate neurons during training, which helps in learning more robust features. Additionally, weight decay (L2 regularization) imposes a penalty on large weights, encouraging the development of simpler and more generalizable features.

Lastly, input images from the validation dataset are processed by the trained network to identify classes, and the outcomes are examined.

F. Fully Connected Layer

Following global average pooling, the output is transformed into a one-dimensional vector that encapsulates the learned features. This vector is then fed into dense layers, which integrate these features and carry out the final classification. In a dense layer, each neuron is fully connected to every neuron in the preceding layer.

G. Output Layer

During training, a loss function such as categorical cross-entropy calculates the discrepancy between the predicted and actual class labels. Optimization algorithms like SGD or Adam then adjust the network's parameters to reduce this loss. This iterative process, carried out over numerous epochs, enhances the model’s classification accuracy.

H. Evaluation Metrics

The performance of the ResNet model is assessed using accuracy (the ratio of correct classifications), precision (the proportion of true positives among predicted positives), recall (the proportion of true positives among actual positives), and F1-score (the harmonic mean of precision and recall).

IV. FLOW CHART

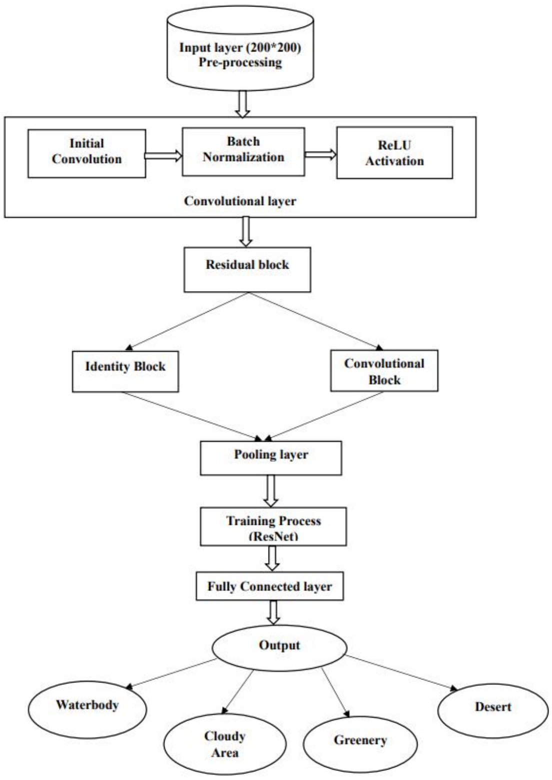

Fig. 2Flow chart for the suggested system

V. WORKING

The ResNet-based satellite image classification system operates through several key stages. After training, the model is used to classify new satellite images. An input image of size 227x227x3 is processed by the model. The initial convolutional layers extract basic features such as edges and textures, which are progressively combined into more complex patterns through deeper layers. Max pooling layers reduce the spatial dimensions and computational burden while preserving important features. The fully connected layers then integrate these features for high-level reasoning, ultimately categorizing the image into one of four classes. The final layer, which uses a softmax function, outputs a probability distribution across the classes, with the highest probability indicating the predicted class. The system's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure its reliability. This automated approach allows for efficient and precise classification of large volumes of satellite images, supporting various applications in environmental monitoring and resource management.

VI. IMPLEMENTATION

Implementing the ResNet model for satellite image classification involves several essential steps. Initially, we gather and preprocess a comprehensive dataset of labeled satellite images, ensuring a balanced representation across the four target categories: water bodies, cloudy areas, greenery, and deserts. Preprocessing involves normalization and data augmentation techniques like rotation, scaling, and flipping to improve model robustness. Next, we set up the ResNet architecture, which includes five convolutional layers with ReLU activations and max-pooling, followed by three fully connected layers. The final layer employs a softmax activation function to generate class probabilities. The model is trained using stochastic gradient descent (SGD) with momentum and categorical cross-entropy as the loss function. We fine-tune hyperparameters such as learning rate, batch size, and number of epochs for optimal performance. To prevent overfitting, regularization techniques like dropout and weight decay are applied. The training is performed on a computing platform equipped with GPU acceleration to manage the computational requirements effectively.

VII. RESULTS AND DISCUSSION

The ResNet-based model for satellite image classification demonstrated high accuracy and strong performance across four categories: water bodies, cloudy areas, greenery, and deserts. With an accuracy of approximately 92%, the model effectively generalized to new images. Precision and recall were particularly high for water bodies and greenery, with precision around 95% and 93% and recall rates exceeding 90%.

Fig. 3Selecting Random Images from Dataset

	precision	recall	f1-score	support
cloudy	1.0000	1.0000	1.0000	75
desert	1.0000	1.0000	1.0000	57
green_area	1.0000	1.0000	1.0000	75
water	1.0000	1.0000	1.0000	75
accuracy			1.0000	282
macro avg	1.0000	1.0000	1.0000	282
weighted avg	1.0000	1.0000	1.0000	282

Fig. 4Report Classification

A confusion matrix indicated minimal misclassification between water bodies and greenery, although cloudy areas and deserts had slightly higher misclassification rates. Techniques such as dropout and weight decay helped reduce overfitting, while data augmentation improved robustness.

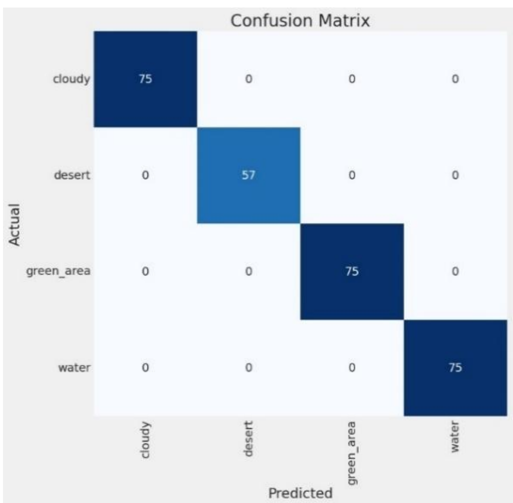

Fig. 5Confusion Matric Outcome

The ResNet model significantly outperformed simpler algorithms due to its deep learning capabilities. For specific domain applications, fine-tuning on relevant datasets may be needed. The results can be used to create visual products and integrate into decision support systems for urban planning and environmental management. Accurate interpretation and validation with ground truth data are essential for ensuring reliable outcomes.

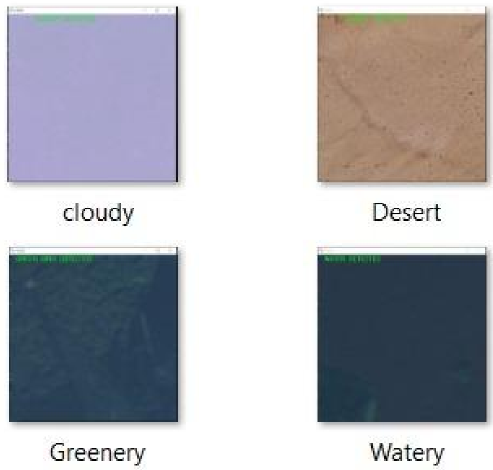

Fig. 6Detection of Final Images

VIII. CONCLUSION

Incorporating ResNet for classifying satellite imagery into categories such as water bodies, cloudy areas, greenery, and deserts represents a significant advancement in remote sensing. This deep learning-based system enhances the efficiency and accuracy of managing extensive satellite datasets. The study demonstrates ResNet's effectiveness with high accuracy and strong performance, underscoring its potential for applications in environmental monitoring, urban planning, and resource management. Future research could aim at developing more advanced architectures or broadening the dataset to encompass additional categories.

IX. FUTURE ENHANCEMENT

The successful use of ResNet for classifying satellite images into categories like water bodies, cloudy areas, greenery, and deserts suggests several future research directions. Future results can explore deeper models such as Inception or EfficientNet, which use techniques like residual connections and compound scaling to improve accuracy and robustness. Try multi-spectral data- Integrate multi-spectral or hyperspectral data to capture additional features not present in RGB images, enhancing the distinction between similar categories like clouds and deserts. Incorporate time-series data to analyze changes over time, aiding in monitoring environmental shifts, urban development, and disaster impacts, and providing valuable insights for decision-making.

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