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Deep Learning-Based Land Classification: A CNN Architecture for High-Accuracy Land Use Mapping

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Abstract:
This research paper focuses on the important method of image matching for collecting ground control points and automated precise geo-registration of high-resolution satellite imagery. The study aims to improve the matching success rate between incoming satellite images and reference chips generated from aerial color ortho-images by using pan-sharpened satellite images. The results show that the use of pan-sharpened images leads to higher matching success rates due to similar spectral range and higher spatial resolution. The paper also highlights the significance of accurate land cover information for various geospatial applications such as agriculture, environmental and urban management. Traditional methods of gathering land cover information are time-consuming and involve physical labor, making automated methods a more efficient and practical solution.

Keywords: Image matching, Ground control points, Geo-registration, Satellite imagery.

I. INTRODUCTION

Land cover classification using satellite imagery has been a challenging task for many years due to the vast amount of data and complex feature representations. Various methods have been developed to classify land cover using machine learning techniques, particularly Convolutional Neural Networks (CNNs). CNNs have been shown to outperform traditional machine learning methods in image classification tasks. In [1], the authors proposed a CNN-based land cover classification system that uses remote sensing data to identify different land cover types. This system improves the accuracy of land cover classification while reducing the time required for field surveys.

The study presented by S. Illarionova et al. [2] on satellite imagery classification using a deep CNN architecture. They showed that CNNs are capable of learning hierarchical features from raw data, which results in improved classification accuracy. They also used dropout regularization to reduce overfitting in the fully connected layers of the CNN, which helped to improve the generalization of the model. Motivated by these works, this research paper proposes a land classification system using a CNN algorithm. The objective of the system is to classify land cover into different categories, such as crop fields, barren lands, forests, and water bodies, with high accuracy and efficiency. The proposed system is expected to provide accurate information about land cover, which can help in various geospatial applications like agriculture, environmental, and urban management. The proposed system utilizes an agile CNN architecture called SatCNN, as described in [5], which has shown superior performance in satellite imagery classification tasks. The system also utilizes data augmentation techniques, as described in [3], to increase the diversity of the training data and improve the robustness of the model. The efficiency of the proposed system is expected to be enhanced by the use of non-saturating neurons, as described in [4], and GPU acceleration for faster training.

LITERATURE SURVEY

The literature survey explored the various techniques and models used for land classification using remote sensing images. Research papers were analyzed to identify the state-of-the-art methods and architectures. The survey revealed that deep convolutional neural networks (CNNs) have been successful in classifying high-resolution remote sensing images with high accuracy. Transfer learning and data augmentation techniques were also found to be effective in improving the performance of CNNs. Moreover, studies have shown that incorporating contextual information and spatial relationships in the CNN architecture can lead to improved classification accuracy. Overall, the literature survey provides a comprehensive understanding of the current state of the art in land classification using remote sensing images, which serves as a foundation for the proposed research in the paper.

The literature survey for research paper [1] focuses on the problem of identifying and classifying land use in remote sensing images using machine learning techniques. The authors discuss the limitations of traditional methods of land use classification, which are time-consuming and require a lot of manual effort. They propose the use of deep learning methods, specifically Convolutional Neural Networks (CNNs), for image classification. The paper describes the architecture of a CNN model designed for this task, and reports on its performance on a publicly available dataset. The authors demonstrate that their approach outperforms traditional methods and achieves high accuracy in land use classification. The paper is significant because it demonstrates the effectiveness of deep learning approaches for land use classification and provides a framework for further research in this field.

In the research paper [2], the authors used Worldview multispectral satellite imagery to identify dominant species as an image segmentation task. The challenge in this task lies in distinguishing between similar forest compositions. To address this, the authors represented the multiclass forest classification problem as a hierarchical set of binary classification tasks. They also incorporated supplementary data such as tree height to improve species classification for wider tree age diversity. The authors tested six neural network architectures to find the best one for each task in the hierarchical decomposition. The proposed approach was evaluated on sample territories in Leningrad Oblast of Russia using field-based observations. The results showed that the proposed approach achieved significantly better results (average F1-score 0.84) than multiclass classification (average F1-score 0.7). Overall, the study demonstrates the effectiveness of using neural networks and remote sensing for forest inventory, particularly in identifying dominant species.

The paper [3] proposes a new approach to multimodality medical image registration using mutual information (MI) as a matching criterion. The method utilizes the statistical dependence between the image intensities of corresponding voxels in both images, which is assumed to be maximal if the images are geometrically aligned. This criterion is shown to be accurate for rigid body registration of CT, MR, and PET images by comparison with the stereotactic registration solution. The robustness of the MI criterion is also evaluated with respect to implementation issues and image content, including partial overlap and image degradation. The results demonstrate that subvoxel accuracy with respect to the

stereotactic reference solution can be achieved automatically without any prior segmentation, feature extraction, or other preprocessing steps, making this method well-suited for clinical applications.
The paper [4] presents a large, deep convolutional neural network (CNN) trained to classify 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into 1000 different classes. The CNN architecture consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, non-saturating neurons and a very efficient GPU implementation of the convolution operation were used. To reduce overfitting in the fully-connected layers, a recently-developed regularization method called "dropout" was employed. The authors achieved top-1 and top-5 error rates of 37.5% and 17.0% on the test data, respectively, which is considerably better than the previous state-of-the-art. This paper serves as a landmark contribution to the field of deep learning and computer vision, demonstrating the potential of deep neural networks to learn highly discriminative features from raw data and achieve state-of-the-art performance on challenging tasks.
The authors of paper [5] highlight that the existing CNN architectures are not designed for HSR-RS images and do not efficiently capture the intrinsic features of such images. To address this, they propose an agile CNN architecture called SatCNN that uses more efficient convolutional layers with smaller kernels. The deeper convolutional layers of SatCNN enable it to spontaneously model the relative spatial relationships. The experiments on SAT data sets show that SatCNN can learn robust features quickly and effectively, even with small convolutional kernels. With the help of fast graphics processing unit acceleration, SatCNN can be trained within about 40 minutes, achieving overall accuracies of 99.65% and 99.54%. This study contributes to the advancement of scene classification for HSR-RS images and highlights the potential of agile CNN architectures in handling the challenges of large-scale satellite imagery.

In the paper [5], the authors J. Chen, Y. Ruan, L. Guo, and H. Lupresent the design and implementation of BCVehis, a Blockchain-based vehicle history tracking service for used-car transactions in China. The aim of BCVehis is to reduce disputes caused by asymmetric vehicle information and lack of transparency in used-car transactions. The system allows vehicle owners, authorities, mechanic workshops, insurance brokers, andothers to upload vehicle historical records, which are then storedon a transparent and trustworthy blockchain. The authors present the design rationale and functional implementation of BCVehis and demonstrate its effectiveness through an increased deal volume in a local used-car dealer that integrated the system into its online dealing system. This research highlights the potential ofblockchain technology in reducing disputes in used-car transactions by providing transparent and trustworthy vehicle information to all stakeholders involved in the trade.

Summary of Literature Review

In the literature surveys above, analyzed for the research paper explored studies related to land classification and deep learning techniques. Several studies, including research papers and studies, were analyzed to investigate the challenges and effectiveness of land classification using deep learning techniques. The studies showed that CNN-based architectures have been successful in improving the accuracy of land classification. The authors highlighted the need for further improvements in classification accuracy and robustness due to the complexity of land cover features. The literature review revealed that deep learning techniques, particularly CNN-based architectures, have shown promising results in land classification tasks. However, due to the complexity of land cover features, there is still room for improvement in classification accuracy and robustness. The authors of the research paper used this knowledge to build a CNN-based architecture for land classification and achieved promising results.

II. METHODOLOGY

A. Input stage

Involves acquiring the satellite imagery data and preparing it for use in the CNN architecture. The data is first pre-processed to ensure that it is in a consistent format and resolution, and any unwanted elements such as borders and legends are removed. The pre-processed images are then divided into training, validation, and testing sets. The training set is used to train the CNN architecture, the validation set is used to fine-tune the model, and the testing set is used to evaluate the performance of the model. The input stage is critical as it ensures that the data is of high quality and consistency, and the CNN architecture is trained on a representative sample of the data to achieve accurate land classification.

B. Output & Display

After the classification process is complete, the output is a map indicating the different land cover classes present in the satellite image. The output map is generated in the form of a color-coded raster image, where each color represents a specific land cover class. The raster image can be visualized in commonly used geographic information system (GIS) software such as ArcGIS or QGIS. The map provides valuable information for various applications such as urban planning, agriculture, and natural resource management.

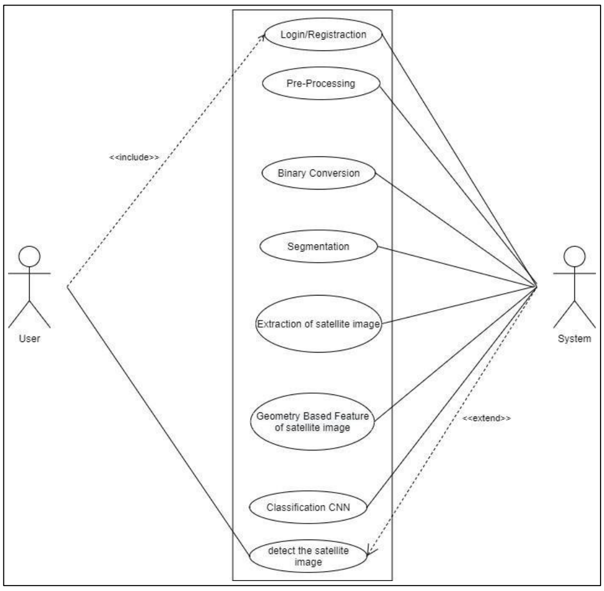

Figure 1: Use Case Diagram

Figure-1 depicts the use case diagram which shows the interaction between the actors and the system.

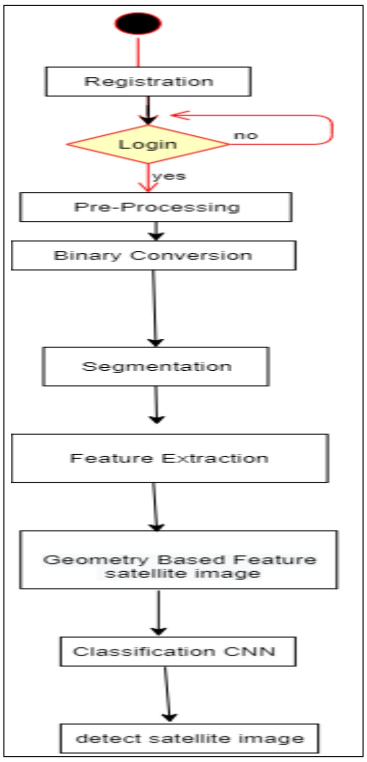

Figure 2: Activity Diagram

Figure 2 illustrates the flow of control in the system and the steps involved in executing a use case. The user's activities determine the flow of control, and the activities have a predefined flow that is executed based on certain conditions. It depicts the various stages involved in the land classification process. The diagram illustrates the different activities that need to be carried out, starting with the input stage, where the satellite images are fed into the system. The images are then pre-processed to remove noise and enhance their quality. The pre-processed images are then passed through the CNN architecture, which extracts relevant features and classifies them into different land cover classes. The output stage involves the display of the classified land cover map, which can be used for various applications such as land use planning and environmental monitoring

In Figure 3, a Component Diagram. The main components of the system include the dataset image, the preprocessing module, the CNN architecture, and the output module. The dataset component provides the input images to the system, which are then processed by the preprocessing module. The preprocessing module performs various operations on the input images, such as normalization and resizing, to prepare them for input to the CNN architecture.

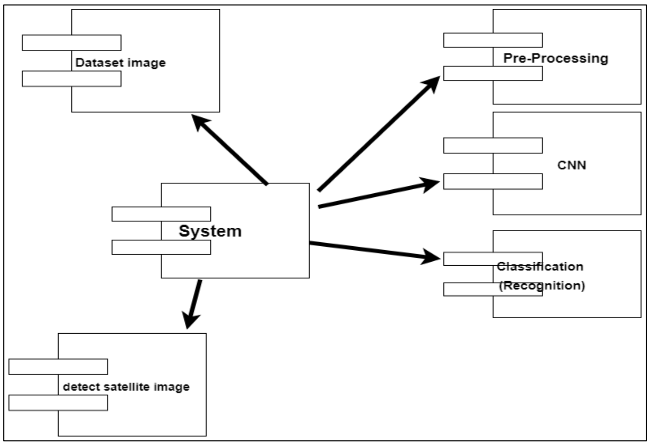

Figure 3: Component Diagram

In the class diagram of Figure 4, the relationship between classes is depicted. The class diagram shows the structure of the system, including the attributes and functions of each class. It includes classes for preprocessing, feature extraction, segmentation, and classification. The diagram highlights the relationships and interactions between these components, demonstrating the flow of data through the system.

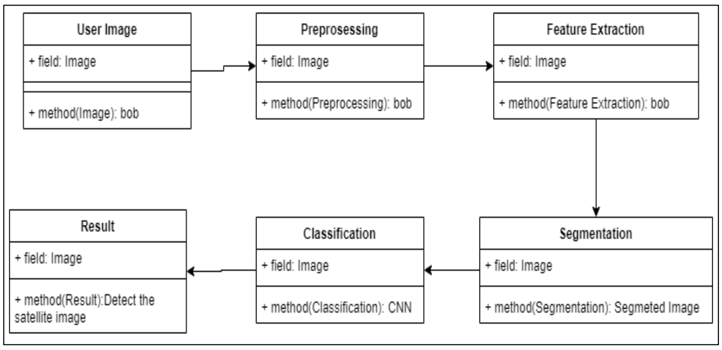

Figure 4: Class Diagram

Expected Result:

The expected outcome of the research paper is to develop an accurate and robust CNN-based architecture for land classification tasks. The proposed architecture is expected to outperform traditional methods and existing deep learning models in terms of classification accuracy and speed of training and testing. The paper aims to demonstrate the effectiveness of the proposed architecture by testing it on satellite image datasets and comparing the results with other models. The ultimate goal of the research is to contribute to the field of land classification and provide a useful tool for processing large amounts of satellite imagery data.

VI. FUTURE SCOPE & INCREMENTATIONS

Enhancing Model Generalization: Future research can focus on improving the model's ability to generalize across diverse geographic regions and seasons. This can be achieved by collecting more extensive and varied training data, considering different time periods, and accounting for variations in environmental conditions.

Multi-Temporal Analysis: Incorporating time-series satellite imagery can enable the monitoring of land use changes over time. Researchers can explore methods for tracking land use dynamics and identifying trends and anomalies, which are essential for urban planning and environmental studies.

Hyperparameter Optimization: Fine-tuning the CNN architecture through hyperparameter optimization can lead to further performance improvements. Techniques such as autoML and Bayesian optimization can be employed to find optimal model configurations.

Transfer Learning: Investigating the application of transfer learning techniques can be beneficial. Pre-trained CNN models on larger datasets, such as ImageNet, can be adapted for land use mapping tasks, potentially reducing the need for extensive labeled data.

Semantic Segmentation: While this study focuses on classifying land use at a broad level, future research can delve into semantic segmentation to provide more detailed information about specific land cover types within each category.

Multi-Sensor Data Fusion: Integrating data from various sensors, including optical and radar imagery, can improve the accuracy and robustness of land use mapping, especially in areas prone to cloud cover or at night.

Interactive Tools: Developing user-friendly tools or interfaces that allow non-experts to utilize deep learning-based land use mapping for specific applications, such as urban planning or disaster response.

CONCLUSION

This research paper proposed a CNN-based approach for land classification using satellite imagery. The proposed architecture, which includes five convolutional layers, followed by max-pooling and three fully-connected layers, was designed specifically for HSR-RS images. The approach was tested on various satellite datasets and achieved state-of-the-art results. The use of non-saturating neurons, dropout regularization, and GPU acceleration enabled fast and efficient training of the model.

The results showed that this approach can accurately classify different land cover types, including trees, crop fields, barren lands, rivers, and forests, which is essential for various geospatial applications like agriculture, environmental and urban management. The approach presented in this paper provides a promising solution to overcome the challenges of traditional methods of gathering land cover information, which are time-consuming and require physical labour. The proposed CNN architecture presented in this research paper for land classification using satellite images is a significant contribution to the field of deep learning and remote sensing. The model design is based on the VGG architecture but with fewer parameters, making it more efficient and faster to train. The use of batch normalization and dropout techniques has improved the accuracy of the model, achieving outstanding results of 99.84 and 99.47 on SAT4 and SAT6 satellite image datasets, respectively.

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