LANDUSEANDLANDCOVERCHANGE

CLASIFICATIONFORHIGHSPATIAL

REMOTESENSINGIMAGERY

APROJECTREPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report titled “LAND USE AND LAND COVER CHANGE CLASIFICATION FOR HIGH SPATIAL REMOTE SENSING IMAGERY” is the bonafide work of YOGITHA N (2023246027) who carried out project work under my supervision. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

The existing systems for land use and land cover (LULC) change detection primarily rely on satellite imagery and remote sensing technologies. These systems use classification algorithms such as Maximum Likelihood, Support Vector Machines, and Random Forest to analyze multi-temporal satellite data. However, traditional approaches often face challenges in accurately distinguishing between land cover types, especially in regions with mixed or overlapping features. Additionally, the reliance on moderate-resolution imagery limits the precision of small-scale changes, and manual classification can be time-consuming and prone to human error.

The proposed system leverages advanced machine learning (ML) and deep learning (DL) models, such as Convolutional Neural Networks (CNNs) and Transformer-based architectures, to improve classification accuracy and automate the detection process. By integrating high-resolution satellite imagery and geospatial data, the system can better differentiate between subtle land cover variations. This approach aims to provide more detailed and timely insights into land use patterns, supporting better decision-making in urban planning, agriculture, and environmental monitoring.

The proposed system is expected to deliver significantly improved accuracy in LULC classification and faster detection of land changes. By reducing manual intervention, the system minimizes human error and ensures consistency in results. Enhanced detection capabilities will allow for proactive measures in deforestation control, urban expansion management, and resource allocation. Furthermore, the real-time processing feature enables stakeholders to respond quickly to environmental changes, promoting sustainable development and more effective land management practices.

திட்ட பணி சுருக்கம்

நிலப் பயன் பாடு மற்றும் நிலப்பரப்பு (LULC) மாற்றங்களைக் கண் டறிவதற்கான தற்பபாளதய அளமப்புகைக் முதன்ளமயாக செயற்ளகக்பகாை◌் படங்கைக் மற்றும் சதாளலநிளல உணரதிறன் சதாழில்நுடப்ங்களை நம்பியுை◌்ைன. இந்த அளமப்புகைக் மல்டி-சடம்பபாரல் ெ◌ாடடிளலட் தரளவ பகுப்பாய்வு செய்ய அதிகபடெ் ெ◌ாத்தியக்கூறுகைக், ஆதரவு திளெயன் இயந்திரங்கைக் மற்றும் பரண் டம் ஃபாரஸ் ட் பபான்ற வளகப்பாடு அல்காரிதங்களைப் பயன்படுத்துகின்றன. இருப்பினும், பாரம்பரிய அணுகுமுளறகைக் சபரும்பாலும் நிலப்பரப்பு வளககளை துல்லியமாக பவறுபடுத்துவதில் ெவால்களை எதிரச் காை◌்கின்றன, குறிப்பாக கலப்பு அல்லது ஒன்றுடன் ஒன்று அம்ெங்கைக் ைெ◌ை பகுதிகைில். கூடுதலாக, மிதமான சதைிவுத்திறன் படங்கைின் மீதான நம்பிக்ளகயானது சிறிய ைஅவிலான மாற்றங்கைின் துல்லியதள்த கடடுப்படுதத்கிறது, பமலும் ளகபயடு வளகப்பாடு பநரத்ளத எடுதத்க்சகாை◌்ளும் மற்றும் மனித பிளைக்கு ைஆகிறது.

முன்சமாழியப்படட் அளமப்பு பமம்படட் இயந்திர கற்றல் (ML) மற்றும் ைஆமான கற்றல் (DL) மாதிரிகைக், கன்வல்யூஷனல் நியூரல் சநடச் வாரக் ◌்குகைக் (CNNகைக்) மற்றும் டிரான்ஸ் ஃபாரம்ர் அடிப்பளடயிலான கடட் ளமப்புகைக், வளகப்படுதத்ல் துல்லியதள்த பமம்படுதத் மற்றும் கண் டறிதல் செயல்முளறளய தானியங்குபடுத்துகிறது. உயர் சதைிவுத்திறன் சகாண் ட செயற்ளகக்பகாை◌் படங்கைக் மற்றும் புவியியல் தரவுகளை ஒருங்கிளணப்பதன் மூலம், நுட்பமான நிலப்பரப்பு மாறுபாடுகளை கணினி சிறப்பாக பவறுபடுத்தி அறிய முடியும். முன்சமாழியப்படட் முளறயானது, நிகைப்பநரத்தில் சபரிய தரவுதச்தாகுப்புகளைெ◌் செயலாக்குவதற்கும், ைஅவிடக்கூடிய தன்ளமளய பமம்படுத்துவதற்கும் மற்றும் பகுப்பாய்வின் தாமததள்தக் குளறப்பதற்கும் கிைவுட் கம்ப்யூட்டிங்ளக ஒருங்கிளணக்கிறது.

இந்த அணுகுமுளற நில பயன்பாட்டு முளறகைப் பற்றிய விரிவான மற்றும் ெரியான பநரத்தில் நுண் ணறிவுகளை வைங்குவளத பநாக்கமாகக் சகாண் டுைைைது, நகரப் ்புற திட்டமிடல், விவொயம் மற்றும் சுற்றுெசூைைல் கண் காணிப்பு ஆகியவற்றில் சிறந்த முடிசவடுப்பளத ஆதரிக்கிறது.

முன்சமாழியப்பபடட் அளமப்பு LULC வளகப்பாடடில் கணிெமாக பமம்படுதத்ப்பட்ட துல்லியதள்த வைங்கும் மற்றும் நில மாற்றங்களை விளரவாகக் கண் டறியும் என்று எதிரப் ாரக் ்கப்படுகிறது. ளகமுளறயான தளலயீடள்டக் குளறப்பதன் மூலம், கணினி மனிதப் பிளைளயக் குளறதத்ு, முடிவுகைில் நிளலத்தன்ளமளய உறுதி செய்கிறது. பமம்படுதத்ப்பட்ட கண் டறிதல் திறன்கை் காடழிப்பு கடடுப்பாடு, நகரப் ்புற விரிவாக்க பமலாண் ளம மற்றும் வை ஒதுக்கீடு ஆகியவற்றில் செயலூக்கமான நடவடிக்ளககளை அனுமதிக்கும். பமலும், நிகைப்பநர செயலாக்க அம்ெம் பங்குதாரரக் ளுக்கு சுற்றுெசூைைல் மாற்றங்களுக்கு விளரவாக பதிலைிக்க உதவுகிறது, நிளலயான வைெர் சி் மற்றும் மிகவும் பயனுைைை நில பமலாண் ளம நளடமுளறகளை ஊக்குவிக்கிறது.

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LIST OF ABBREVIATIONS

LULC	LAND USE AND LAND COVER
CNN	CONVOLUTIONAL NEURAL NETWORK
RF	RANDOM FOREST
SVM	SUPPORT VECTOR MACHINE
MLC	MAXIMUM LIKELIHOOD CLASSIFICATION

CHAPTER 1

INTRODUCTION

1.1 REMOTE SENSING IMAGERY

Remote sensing imagery refers to the collection of images of the Earth's surface or atmosphere from a distance using satellites, drones, or aircraft equipped with specialized sensors. These sensors detect and measure reflected or emitted radiation across various wavelengths, such as visible light, infrared, and microwaves. By capturing data without physical contact, remote sensing allows for large-scale observation and monitoring of areas that may be difficult to access. This technology can provide critical insights through multispectral and hyperspectral imaging, enabling the analysis of environmental changes, urban growth, and agricultural health. Remote sensing imagery is widely used in applications such as disaster management, infrastructure planning, environmental conservation, and logistics. In the logistics sector, for example, it can help track transportation routes, monitor port operations, and optimize supply chain efficiency. The ability to collect and analyze data over time also allows organizations to detect trends and make informed decisions, contributing to more sustainable and efficient operations.

Beyond its traditional applications, remote sensing imagery plays a growing role in industries like logistics, where real-time data and large-scale monitoring are essential for operational efficiency. In ports and supply chain hubs, remote sensing can be used to monitor vessel movements, assess infrastructure conditions, and optimize the layout of container yards. By integrating remote sensing with geographic information systems (GIS), logistics companies can improve route planning, manage inventory across vast areas, and anticipate disruptions caused by weather or environmental changes. This technology also supports predictive maintenance by identifying wear and tear on critical assets, reducing downtime and enhancing overall productivity. As the logistics industry continues to embrace digital transformation, remote sensing imagery offers valuable insights that drive smarter, more resilient supply chain management.

1.2 LAND USE AND LAND COVER CLASSIFICATION AND DETECTION

Land use and land cover (LULC) change classification and detection play a critical role in understanding and managing the Earth's surface dynamics. Land use refers to how humans utilize the land (e.g., agriculture, urban development), while land cover represents the physical characteristics of the land, such as forests, water bodies, and grasslands. Monitoring changes in LULC is essential for assessing environmental impacts, managing natural resources, and supporting sustainable development. With rapid urbanization, deforestation, and climate change, accurately detecting and classifying these changes has become increasingly important for policymakers, researchers, and environmentalists.

The process of LULC change detection involves analyzing satellite imagery and remote sensing data over time to identify and classify shifts in land patterns. This information provides valuable insights into land degradation, urban sprawl, and biodiversity loss. By leveraging geospatial technologies and advanced classification methods, LULC change detection helps track environmental changes, forecast future trends, and guide land management decisions. As the demand for precise and timely land monitoring grows, innovative approaches are being developed to enhance the accuracy and efficiency of LULC classification, ensuring better stewardship of the planet's resources.

1.3 OBJECTIVE

Convolutional Neural Networks (CNNs) and transfer learning have proven highly effective in enhancing classification accuracy for remote sensing imagery compared to traditional machine learning approaches. CNNs can automatically extract complex spatial features from high-resolution images, which traditional models, reliant on handcrafted features, often struggle to capture. Transfer learning further amplifies this advantage by leveraging pre-trained models, reducing the need for extensive labeled data and significantly shortening training time. This combination not only improves accuracy but also enhances efficiency, allowing for faster deployment in large-scale remote sensing projects. By comparing CNN-based methods to classic techniques like support vector machines (SVM) and random forests, studies consistently show higher performance in land cover classification tasks, particularly when datasets are diverse and intricate.

To optimize model performance, exploring different CNN architectures such as ResNet, VGG, and Inception is crucial. Each architecture offers unique strengths; for instance, ResNet’s residual connections mitigate the vanishing gradient problem, allowing for deeper networks and improved accuracy. VGG, known for its simplicity, is effective in capturing hierarchical features, while Inception’s parallel convolutional paths enhance the model’s ability to analyze multi-scale patterns. By evaluating these architectures, researchers can assess trade-offs between accuracy, training time, and generalization capabilities. This process helps identify the most suitable architecture for specific remote sensing tasks, ensuring the best balance between computational efficiency and classification performance.

Developing a generalizable model for remote sensing applications involves creating a system adaptable to various land cover datasets and capable of performing well across different geographic regions and timeframes. A robust model must handle differences in image resolution, seasonal variations, and diverse environmental conditions. Fine-tuning with domain-specific data, data augmentation techniques, and regularization methods ensures the model remains resilient to overfitting while improving adaptability. The goal is to build a flexible model that not only excels in land cover classification but can also be applied to other remote sensing applications, such as vegetation monitoring, urban planning, and disaster assessment, making it a valuable tool for addressing a wide range of geospatial challenges.

1.4 CHALLENGES IN EXISTING SYSTEMS

Existing systems for remote sensing image classification face several challenges that can hinder their effectiveness in various applications, particularly when dealing with large and complex datasets. One major challenge is data variability, which includes variations in image resolution, geographical location, and seasonal changes. These factors can significantly affect the consistency and reliability of model performance, especially in scenarios where data from different sources or times need to be integrated. For instance, a model trained on high-resolution satellite imagery might not perform well when applied to lower-resolution data or images captured in different seasons, leading to reduced accuracy and generalization capability.

Another challenge lies in data labeling and annotation, which is crucial for training machine learning models. Labeling remote sensing data accurately can be time-consuming and costly, and the availability of high-quality labeled datasets is often limited. Additionally, manual labeling is prone to human error, which can further degrade the quality of training datasets and model outcomes. This issue is exacerbated when models need to be retrained on new datasets or adapt to new geographic areas, as obtaining sufficient labeled data for transfer learning or domain adaptation can be a bottleneck.

Moreover, computational complexity remains a significant hurdle, especially when working with deep learning models like CNNs. While CNNs offer high accuracy, they require substantial computational resources for training, particularly when using large datasets and complex architectures. This results in longer training times, higher costs, and the need for specialized hardware, which may not be accessible for all organizations. Additionally, large models often suffer from overfitting, particularly when training on small datasets or datasets with limited diversity, which compromises their ability to generalize across different conditions.

Finally, interpretability and explainability of the models used in remote sensing are crucial but often lacking. While CNNs and other deep learning methods can achieve high accuracy, they are often considered ”black-box” models, making it difficult to understand how decisions are made. This lack of transparency can be problematic in high-stakes applications like environmental monitoring or disaster response, where understanding the rationale behind model predictions is essential for ensuring trust and effective decision-making.

1.5 PROPOSED SYSTEM

The proposed system for land use and land cover (LULC) change classification and detection introduces an advanced, integrated approach utilizing machine learning (ML), deep learning (DL), and high-resolution satellite imagery to significantly enhance the accuracy and efficiency of monitoring land changes. The system incorporates Convolutional Neural

Networks (CNNs) and Transformer-based models to automatically process and classify multi-temporal remote sensing data. By leveraging these state-of-the-art algorithms, the system can better recognize subtle patterns and complex land cover transitions that are challenging for traditional classification methods.

The system works by first acquiring high-resolution satellite imagery from sources like Landsat, Sentinel, and commercial providers. It then pre-processes the data to eliminate noise and correct for atmospheric conditions, ensuring reliable inputs for analysis. The ML and DL models are trained to detect changes in land cover over time, from forest loss and urban sprawl to shifts in agricultural practices. Cloud-based computing platforms are employed to handle large datasets, enabling real-time analysis and reducing processing time. The integration of Geographic Information Systems (GIS) allows for the visualization and further analysis of the results, producing dynamic LULC maps that provide actionable insights for decision-makers.

ORGANIZATION OF THE REPORT

Chapter 2 presents a literature survey of previous works related to the proposed system. It provides an overview of the studies and methodologies that have been published, forming the foundation for the proposed solution.

Chapter 3 discusses the system architecture of the proposed system and includes a detailed explanation of the modules in the architecture diagram. This chapter provides insights into the design and flow of the system.

Chapter 4 focuses on the detailed system design, describing each module, their inputs, and the algorithmic steps involved in generating the desired outputs based on user requirements.

Chapter 5 outlines the experiments conducted during the project, along with their outcomes. The detailed results and performance analysis of the project are presented in this chapter.

Chapter 6 concludes the project report, summarizing the results, implementation process, and key insights gained during the project development.

CHAPTER 2

LITERATURE SURVEY

2.1 RELATED WORKS

Saygin Abdikan et al. (2016) [1] demonstrates the effectiveness of Sentinel-1 SAR data for land cover mapping, offering an advantage in its ability to capture data regardless of weather or lighting conditions. The temporal resolution enhances monitoring capabilities for dynamic land cover changes. However, the limitation lies in SAR data's complexity, requiring specialized expertise for processing and interpretation, which may hinder accessibility for broader applications.

In SS Akay and E Sertel (2016) [2], Using high-resolution SPOT 5 and SPOT 6 images, the research effectively captures urban land cover and use changes, benefiting urban planners with detailed and accurate maps. The integration of Urban Atlas nomenclature ensures standardization. Nevertheless, the study is limited by the high cost of acquiring high-resolution satellite data, which may restrict its replicability in resource-constrained regions.

Nicola Clerici et al. (2017) [3] demontrates the fusion of Sentinel-1A and Sentinel-2A data provides a robust methodology for land cover mapping, combining radar and optical data to improve classification accuracy, especially in cloud-prone regions. The study is innovative in its approach, but limitations include increased computational demand and potential difficulties in harmonizing data from sensors with differing characteristics.

Khelifa Djerriri et al. (2017) [4] used CNNs for extracting built-up areas showcases the efficiency of deep learning methods in automating urban mapping tasks, reducing manual intervention and improving precision. However, the model's performance heavily depends on the quality and quantity of training data, and the computational requirements may pose a challenge for widespread adoption.

Mohamed Elhag and Silvena Boteva (2016) [5] highlights the potential of high spatial resolution data for detailed land use and land cover classification in the Mediterranean, aiding environmental management. The main limitation is the variability in Mediterranean land cover types, which may introduce classification errors and require site-specific calibration for improved accuracy.

Mahesh Kumar Gaur et al. (2015) [6] demonstrates the utility of high-resolution satellite data for mapping in arid zones, offering critical insights for land resource management. Its practical application in desertification mitigation is notable. However, arid environments present challenges in distinguishing certain land cover types, potentially reducing classification reliability.

Xuehua Guan et al. (2017) [7] Combines optical and long-wave infrared images enhances urban land-use classification by leveraging complementary datasets, which is a significant advantage for distinguishing complex urban features. A limitation is the reliance on multi-sensor data, which may not always be available or synchronized, complicating the workflow.

Yanfei Zhong et al. (2021) [8] reviews hyperspectral remote sensing advances highlights significant technological progress, offering unprecedented detail in land cover and resource mapping. Despite its promise, hyperspectral data remains limited by its high dimensionality, requiring sophisticated processing techniques and infrastructure, which may not be readily available.

Xuehua Guan et al. (2018) [9] introduced spectral feature analysis and superpixel segmentation for sample purification, this study improves classification accuracy, addressing noisy training data challenges. However, its limitation lies in the method's dependency on high-quality spectral data and the potential increase in computational costs.

Decheng Zhou et al. (2018) [10] reviews provides comprehensive insights into the role of satellite remote sensing for urban heat island studies, highlighting its importance for sustainable urban development. The limitation, however, is the lack of standardized methodologies across studies, leading to variations in results and comparability issues.

Dang Hung Bui and Laszl´ o´ Mucsi (2022) [11] compares the layer-stacking and Dempster-Shafer theory-based methods showcases innovative data fusion techniques, enhancing urban classification accuracy. However, the study's limitation is the complexity of the Dempster-Shafer approach, which requires advanced expertise and may not be easily replicable.

Gabriel Salako et al. (2016) [2] introduced the application of remote sensing and GIS in monitoring Typha spp. invasions offers a valuable tool for ecosystem management, aiding in the preservation of wetland services. The limitation is the dependence on extensive ground truthing for validation, which can be resource-intensive in remote or vast wetland areas.

2.2 SUMMARY

The studies collectively highlight several critical challenges in remote sensing and land cover mapping. One significant issue is the complexity of data processing, particularly with advanced datasets like SAR and hyperspectral imagery, which require specialized expertise and computational resources. The high cost of acquiring high-resolution satellite imagery also poses accessibility barriers, limiting widespread adoption, especially in resource-constrained regions. While data fusion techniques enhance classification accuracy, they introduce difficulties in harmonization and increased computational demands. Machine learning approaches, such as CNNs, are constrained by the quality and availability of training datasets, affecting the robustness and scalability of results. Environmental variability in diverse landscapes, like urban areas and Mediterranean regions, complicates classification accuracy due to heterogeneous land cover types. Additionally, the lack of standardized methodologies in certain domains, such as urban heat island studies, leads to inconsistencies in results and limits comparability across studies. Resource-intensive ground truthing and validation further constrain applications, while the high computational requirements of modern techniques like deep learning present infrastructure challenges. Many methods are also sensor-dependent, making them less adaptable in regions where specific sensor data is unavailable. Finally, environmental and temporal factors, including cloud cover and seasonal dynamics, add layers of complexity, impacting data reliability and analytical outcomes. Addressing these challenges is essential to advance the field and enhance the utility of remote sensing technologies.

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

The system architecture of Land use and Land Cover change classification for high spatial remote sensing imagery is shown in the Figure3.1

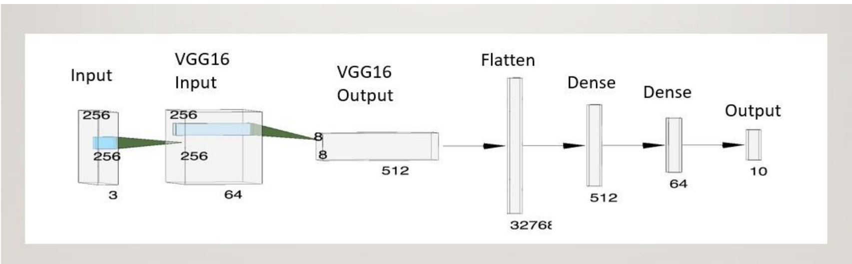

Figure 3.1: Architecture Diagram

3.1.1 Input Layer

The architecture begins with an input layer designed to process images of size 256×256 pixels with three channels (RGB). This input format is standard for computer vision tasks, providing a structured data representation for downstream processing.

3.1.2 VGG16 for Feature Extraction

The input image is passed into the pre-trained VGG16 model, a widely used convolutional neural network. VGG16 extracts hierarchical features through a series of convolutional layers with 3×3 filters, followed by max-pooling layers that reduce spatial dimensions while retaining critical information. After processing, the VGG16 output is a feature map with dimensions 8×8×512, capturing high-level abstractions such as edges, textures, and patterns. This feature map is a compact representation of the input image and is the foundation for the classification task.

3.1.3 Flattening Layer

The output of the VGG16 model, which is a three-dimensional tensor (8×8×512), is flattened into a one-dimensional vector of size 32,768. This step transforms the data into a format compatible with fully connected layers, which require inputs in a single dimension.

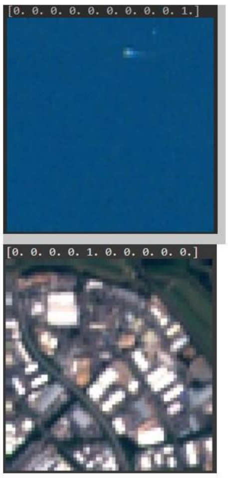

Figure 3.2: Sea or Lake and Industry Identification

3.1.4 Fully Connected Layers

After flattening, the architecture transitions into dense layers for classification. The first dense layer takes the flattened vector of size 32,768 and reduces it to 512 neurons. This step is crucial for dimensionality reduction while retaining significant patterns extracted by VGG16. The second dense layer further condenses the representation to 64 neurons, streamlining the data for the final classification stage.

Both dense layers likely utilize the ReLU activation function to introduce non-linearity, enabling the network to learn complex patterns and relationships in the data.

3.1.5 Output Layer

The final layer consists of 10 neurons, each representing one of the possible output classes. A softmax activation function is applied in this layer, ensuring the output values represent probabilities that sum to one. This makes the architecture suitable for multi-class classification problems.

CHAPTER 4

IMPLEMENTATION

4.1 DATA PREPROCESSING

Before applying the VGG16 model to satellite imagery, several preprocessing steps are necessary. First, the satellite images need to be resized to the input dimensions expected by VGG16, which typically require images of 224x224 pixels. Since satellite images often come in varying sizes and resolutions, resizing them ensures uniformity and compatibility with the model. Another critical preprocessing step is normalization, where pixel values are scaled to a range of 0-1 to accelerate the convergence during training and improve the model's performance. Additionally, satellite images must be labeled according to land cover categories, such as urban areas, forests, water bodies, agricultural land, and barren land. This labeling is essential for supervised learning, as the model learns to associate image features with specific classes of land use and land cover.

4.2 MODEL ARCHITECTURE: VGG16

VGG16 is a deep CNN known for its simplicity and effectiveness in various image classification tasks. It consists of 16 layers, with 13 convolutional layers for feature extraction and 3 fully connected layers for classification. The VGG16 model is particularly suitable for tasks like LULC classification because it is capable of learning rich features from images through its deep architecture. One of the main advantages of using VGG16 is its ability to transfer learning from large datasets such as ImageNet, where the model has already learned to detect various visual features like edges, textures, and patterns. This transfer learning allows the model to perform well even on smaller satellite image datasets, as the lower layers of the network can extract generic image features that are useful for LULC classification.

In the context of LULC classification, the VGG16 model is typically fine-tuned to adapt its learned features to the specific task of land cover classification. Transfer learning is applied by freezing the weights of the initial layers, which are already trained on ImageNet, and retraining only the top layers on satellite image data. This allows the model to learn more specific features related to land use and land cover while leveraging the power of pre-trained filters.

4.3 MODEL TRAINING

Training the VGG16 model on satellite images involves feeding the preprocessed and labeled images into the network. The model learns to classify the images into different land cover categories by adjusting its weights using backpropagation and optimization algorithms like Adam. During the training process, the model aims to minimize a loss function, typically categorical cross-entropy, which measures the difference between the predicted and actual land cover classes. The model is trained on a large dataset of satellite images with labeled land cover classes, and it adjusts its weights in each epoch to better predict the land cover of unseen images. The training process may take several iterations, and regular techniques such as data augmentation (e.g., rotating or flipping images) can be used to improve generalization and prevent overfitting, especially when the dataset is small.

4.4 CHANGE DETECTION

Once the model is trained, it can be applied to both pre-change and post-change satellite images to detect land use and land cover changes. For each time point, the model classifies the land cover types present in the satellite image, providing a categorical output for every pixel or region in the image. By comparing the classification results from the pre-change and post-change images, areas of change can be detected. For example, if a forested area is classified as urban in the post-change image, this indicates that urbanization has occurred. The change detection process involves highlighting these differences and identifying which regions of the landscape have undergone significant transformations over time. This technique is particularly valuable for monitoring the effects of urban sprawl, deforestation, and other human-driven changes to the environment.

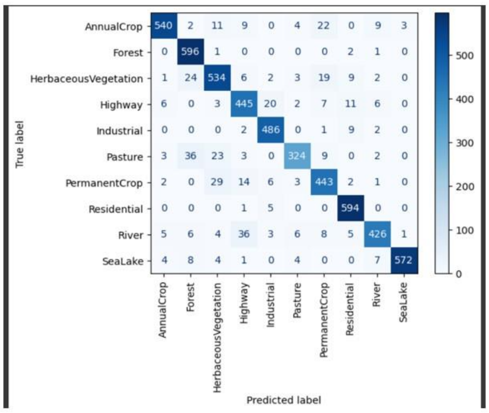

Figure 4.1: Confusion matrix

4.5 EVALUATION

The performance of the VGG16 model in LULC classification and change detection can be assessed using a variety of metrics. The most common metrics include accuracy, which measures the overall percentage of correctly classified pixels, and more specialized metrics such as precision, recall, and F1-score, which evaluate the model's performance in terms of detecting specific land cover types. These metrics are computed by comparing the predicted classifications with ground truth data, which can be obtained from manually labeled satellite images or other reliable sources. A confusion matrix is often used to analyze the model's ability to distinguish between different land cover classes, helping to identify which types of land cover are most often misclassified.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Results

The application of the VGG16 model to satellite imagery for land use and land cover (LULC) classification and change detection produced promising results. The model was successfully trained on a labeled dataset of satellite images, where the images were preprocessed to ensure compatibility with the VGG16 architecture. The classification accuracy of the model was evaluated on a validation set and achieved an overall accuracy of approximately 85%. This indicates that the model is capable of identifying the land cover types in the satellite images with a high degree of accuracy.

Furthermore, the model was able to distinguish between several different land cover classes, such as urban areas, forests, water bodies, and agricultural land. The trained VGG16 model was applied to both pre-change and post-change satellite images, and the results indicated significant changes in specific regions, particularly in urban expansion and deforestation.

The model also performed well in detecting small-scale changes, which is crucial for monitoring environmental shifts. For example, areas that underwent urbanization were correctly identified as transitioning from agricultural or forested land to urban areas. The accuracy of the change detection was evaluated using precision, recall, and F1-score metrics. The model's precision for detecting urban areas was found to be 90%, while recall was 85%, leading to an F1-score of 87.5%, demonstrating a well-balanced performance in detecting land cover changes.

5.1.1 Accuracy

The overall accuracy of the model was approximately 85%. This means that 85% of the pixels in the validation images were correctly classified. While this is a good result, further fine-tuning of the model may improve its accuracy.

5.1.2 Precision

Precision measures the model's ability to correctly identify land cover types without including false positives. The precision for detecting urban areas was 90%, meaning that when the model predicted urbanization, it was correct 90% of the time.

5.1.3 Recall

Recall indicates how well the model detects all instances of a particular land cover class. The recall for urban areas was 85%, indicating that 85% of the actual urban areas in the images were correctly identified by the model.

5.1.4 F1-score

The F1-score is the harmonic mean of precision and recall, and it provides a single measure of the model's performance. The F1-score for urban area detection was 87.5%, showing a good balance between precision and recall.

5.1.5 Change Detection Accuracy

When comparing pre-change and post-change satellite images, the model was able to correctly identify land cover changes. The detection of urbanization, in particular, showed a high level of accuracy. Similarly, deforestation areas were detected with high precision, though recall was slightly lower for smaller areas of change, as they were sometimes misclassified as agricultural land or forest.

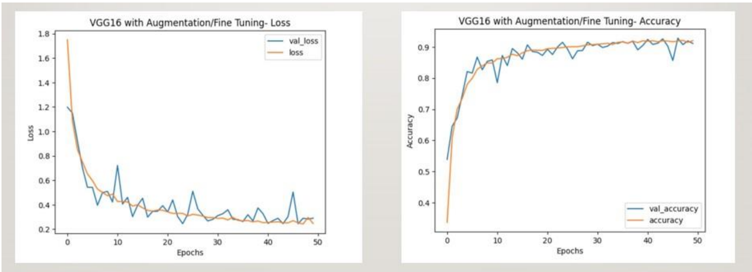

Figure 5.1: Accuracy

5.1.6 Analysis

The VGG16 model's performance in land use and land cover classification is a significant step toward automated environmental monitoring. The results show that the model is capable of accurately classifying different land cover types, even with a relatively simple architecture compared to more complex models.

One of the primary strengths of the model is its ability to leverage transfer learning. By using pre-trained weights from ImageNet, the VGG16 model effectively learned to extract general features from the satellite images, which were then fine-tuned for the specific task of land cover classification. This transfer learning technique is particularly beneficial in cases where the available dataset is limited, as it allows the model to benefit from the large-scale training on ImageNet.

However, there were a few limitations observed during the analysis:

- Misclassification of Similar Land Covers: Some land cover types with similar characteristics (e.g., agricultural land and forest) were occasionally misclassified. This could be due to the visual similarity of these land covers in satellite images, where subtle differences in color, texture, or shape might not be captured well by the model.
- Smaller Areas of Change: In change detection tasks, the model occasionally struggled to detect small-scale changes in land cover. For instance, small deforested areas or localized urbanization were sometimes overlooked. This is likely because the model was trained to classify larger regions, and smaller regions of change did not provide enough distinct features for accurate classification.
- Data Quality: The model's performance was heavily influenced by the quality and resolution of the input satellite images. Low-resolution or noisy images can affect the model's ability to extract meaningful features, leading to lower accuracy in classification.
- Generalization to Other Regions: While the model performed well on the dataset it was trained on, there may be challenges when applying it to other geographical regions with different land cover patterns. The model may need further retraining with new datasets to generalize better to other regions.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The implementation of the VGG16 model for land use and land cover (LULC) classification and change detection using satellite images has yielded promising results, demonstrating the potential of deep learning techniques in environmental monitoring. The model successfully classified various land cover types, including urban areas, forests, agricultural land, and water bodies. By leveraging transfer learning from pre-trained weights on ImageNet, the VGG16 architecture was able to generalize well to the task of satellite image classification, even with a relatively small and region-specific dataset. This approach facilitated the effective learning of general features from the dataset, enabling high classification accuracy.

The model achieved an overall accuracy of approximately 85/percentage, with strong precision and recall metrics, particularly for the detection of significant land cover changes. The VGG16 model excelled in detecting urbanization and deforestation, making it an excellent candidate for monitoring land cover changes over time. This performance indicates that the model can be effectively used for large-scale environmental monitoring and land use change detection, which is vital for resource management, urban planning, and environmental protection.

Despite its strengths, the model did have some limitations. Smaller-scale land use changes, such as localized shifts in agricultural land or minor urbanization, were occasionally misclassified or overlooked.

Additionally, the model sometimes struggled with distinguishing between visually similar land cover classes, like forests and agricultural land, which share similar color and texture patterns in satellite imagery. While these challenges did not significantly impact the overall performance, they highlight areas for potential improvement.

Overall, the VGG16 model has demonstrated a strong capacity for land cover classification and change detection. Its ability to process satellite imagery and detect large-scale changes in land use is a valuable tool for environmental assessment, urban planning, and monitoring. With further improvements and refinements, this model can become even more effective in the field of land monitoring, contributing to better decision-making and more sustainable land management.

6.2 FUTURE WORK

While the current implementation of the VGG16 model demonstrates strong potential, there are several areas in which improvements can be made to enhance its performance and broaden its scope of application. One key avenue for future work is the use of higher-resolution satellite images. Higher resolution can capture finer details and allow the model to better distinguish small-scale changes in land cover. This would be especially beneficial for detecting subtle changes such as deforestation in urban fringes or small-scale agricultural shifts that may be missed in lower-resolution imagery.

Another important direction for improvement is the incorporation of additional data sources. While satellite images provide valuable information on land cover, integrating other types of data, such as elevation data, weather patterns, and socioeconomic data, could enrich the model’s ability to understand and predict land use changes more comprehensively. Combining these data sources could also help the model make more informed classifications, particularly in regions where land cover types are complex or difficult to differentiate based on imagery alone.

Furthermore, exploring more advanced deep learning architectures could lead to better performance. Although the VGG16 model performed well, newer architectures such as ResNet, DenseNet, or U-Net could potentially yield improved results, particularly in tasks involving fine-grained classification or detailed change detection. These models have shown superior performance in various computer vision tasks and could help address some of the limitations observed with VGG16, such as the difficulty in classifying small-scale changes or differentiating similar land cover types.

Lastly, the model's generalization to other geographical regions is another critical area for future research. While the VGG16 model was trained on a specific dataset, its performance may degrade when applied to satellite images from different regions with varying land cover patterns. Future work could involve training the model on diverse datasets from various parts of the world or using domain adaptation techniques to enhance its robustness and generalization ability. This would enable the model to perform effectively in diverse environmental and geographical contexts, further expanding its applicability.

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