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Satellite Image Classification using cnn and irl

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ABSTRACT

Satellite image classification plays a crucial role in various domains including agriculture, urban planning, disaster response, and environmental monitoring. However, it often relies heavily on large manually labeled datasets for accurate classification. In this research paper, we propose a novel method that combines Convolutional Neural Networks (CNNs) with Inverse Reinforcement Learning (IRL) to alleviate the burden of labeling while enhancing classification accuracy.

Keywords: **Image classification,Convolutional Neural Networks (CNNs),Inverse Reinforcement Learning (IRL), Deep learning,Data labeling,Feature extraction,Pattern recognition,Data scarcity**

I.INTRODUCTION

Satellite image classification is crucial in multiple domains such as agriculture, urban planning, disaster response, and environmental monitoring. Traditional methods, specifically Convolutional Neural Networks (CNNs), have been widely employed for this purpose. However, they pose a significant challenge, which is the requirement for a substantial amount of accurately labeled data. Manually labeling these datasets is time-consuming and expensive, presenting a major hurdle. The conventional approach utilizing CNNs excels at identifying patterns in satellite images. Nevertheless, it suffers from a few drawbacks:

- Labeling Challenge: The process of having human experts meticulously label images is not only expensive but also prone to errors.
- Scaling Issues: As the datasets grow larger or when multiple classification tasks are involved, the demand for labeled data increases exponentially, resulting in delays.
- Adaptation to Changing Conditions: CNNs often struggle to adapt to varying conditions encountered in satellite imagery without extensive labeled datasets.
- Adapting to Changing Conditions in Satellite Imagery: Convolutional Neural Networks (CNNs) often encounter difficulties in adapting to dynamic conditions presented in satellite imagery, particularly in the absence of extensive labeled datasets.
- Constraints on Resources and Budget: The collection and annotation of large datasets can present formidable challenges, especially for smaller organizations or regions with limited resources and budgetary constraints. To tackle these challenges, we introduce an innovative approach that combines Convolutional Neural Networks (CNNs) with Inverse Reinforcement Learning (IRL). This intelligent solution minimizes the need for extensive manual labeling, improving accuracy and reducing costs. By harnessing the image feature recognition capabilities of CNNs and the learning prowess of IRL, our method autonomously uncovers vital features in satellite images and learns from them through reinforcement learning, mirroring expert behavior. The goal is to reduce our dependence on extensive labeled datasets, ushering in a positive transformation in satellite image classification. 7 This document aims to thoroughly explore our CNN-IRL model, elucidating how these components work in synergy to enhance the efficiency and accessibility of satellite image classification .

II.LITERATURE SURVEY:

Satellite image classification has been a subject of extensive research due to its significance in various applications such as land cover mapping, environmental monitoring, and disaster management. Traditional methods often rely on supervised learning algorithms, where models are trained on labeled datasets. However, these approaches have limitations, particularly in scenarios where obtaining labeled data is resource-intensive and impractical. Recent advancements in deep learning, particularly

Convolutional Neural Networks (CNNs), have shown promise in automating feature extraction from satellite imagery, improving classification accuracy.

CNNs in Satellite Image Classification: The utilization of CNNs in satellite image classification has gained prominence in recent years. These networks are well-suited for capturing hierarchical features and spatial dependencies within satellite imagery, providing superior performance compared to traditional methods. Researchers have explored various CNN architectures, adapting them to the specific challenges posed by satellite data, such as high dimensionality and spatial heterogeneity.

Inverse Reinforcement Learning in Image Analysis: Inverse Reinforcement Learning (IRL) has been successfully applied in various domains, including robotics and computer vision. In the context of image analysis, IRL offers a unique approach by learning from expert demonstrations. The integration of IRL with CNNs has shown promise in enhancing model generalization and decision-making capabilities. However, its application to satellite image classification remains relatively unexplored in the existing literature.

Satellite Image Classification Challenges: Satellite image classification faces challenges such as data scarcity, class imbalance, and the need for accurate feature extraction. Traditional supervised learning approaches may struggle in scenarios where labeled datasets are limited. This has motivated researchers to explore alternative methods, including transfer learning and unsupervised learning techniques.

Comparative Analysis of Classification Algorithms: Studies comparing the performance of different classification algorithms in the context of satellite imagery have been conducted. Support Vector Machines (SVM), Random Forests, and other traditional machine learning algorithms have been benchmarked against CNNs. These comparisons highlight the strengths and weaknesses of each method and provide valuable insights into their applicability to specific tasks.

Remote Sensing Applications and Impact: The impact of satellite image classification extends to diverse fields, including agriculture, urban planning, and environmental monitoring. The literature emphasizes the importance of accurate classification for informed decision-making in these domains. As advancements in image analysis techniques continue, the potential for addressing real-world challenges and contributing to sustainable development becomes increasingly apparent.

III.OBJECTIVES:

Implement a novel approach by integrating Inverse Reinforcement Learning (IRL) with Convolutional Neural Networks (CNNs) for satellite image classification.

Leverage IRL to allow the model to learn from expert demonstrations and infer the underlying reward structure guiding decision-making in satellite image classification.

Compare the performance of the proposed IRL-based CNN model with traditional supervised learning algorithms, such as Support Vector Machines (SVM), Random Forests, and conventional CNNs.

IV.PROPOSED METHODOLOGY

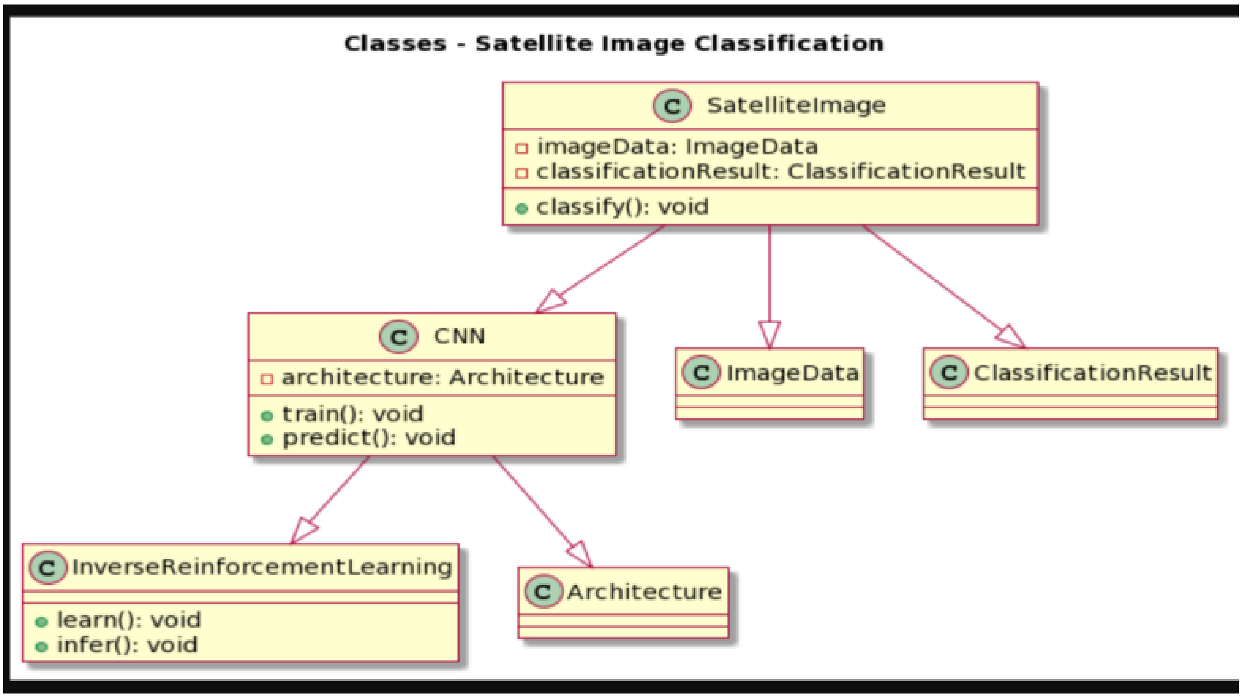
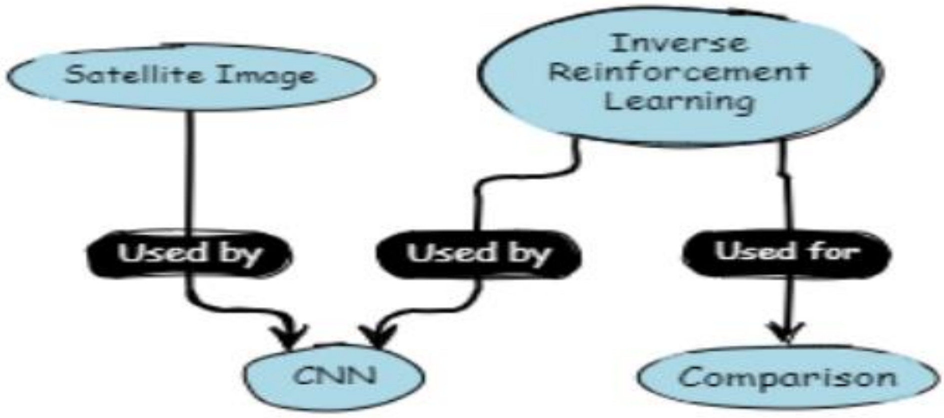


fig 1: Class diagram for satellite Image Classification

- **Architecture Diagram**



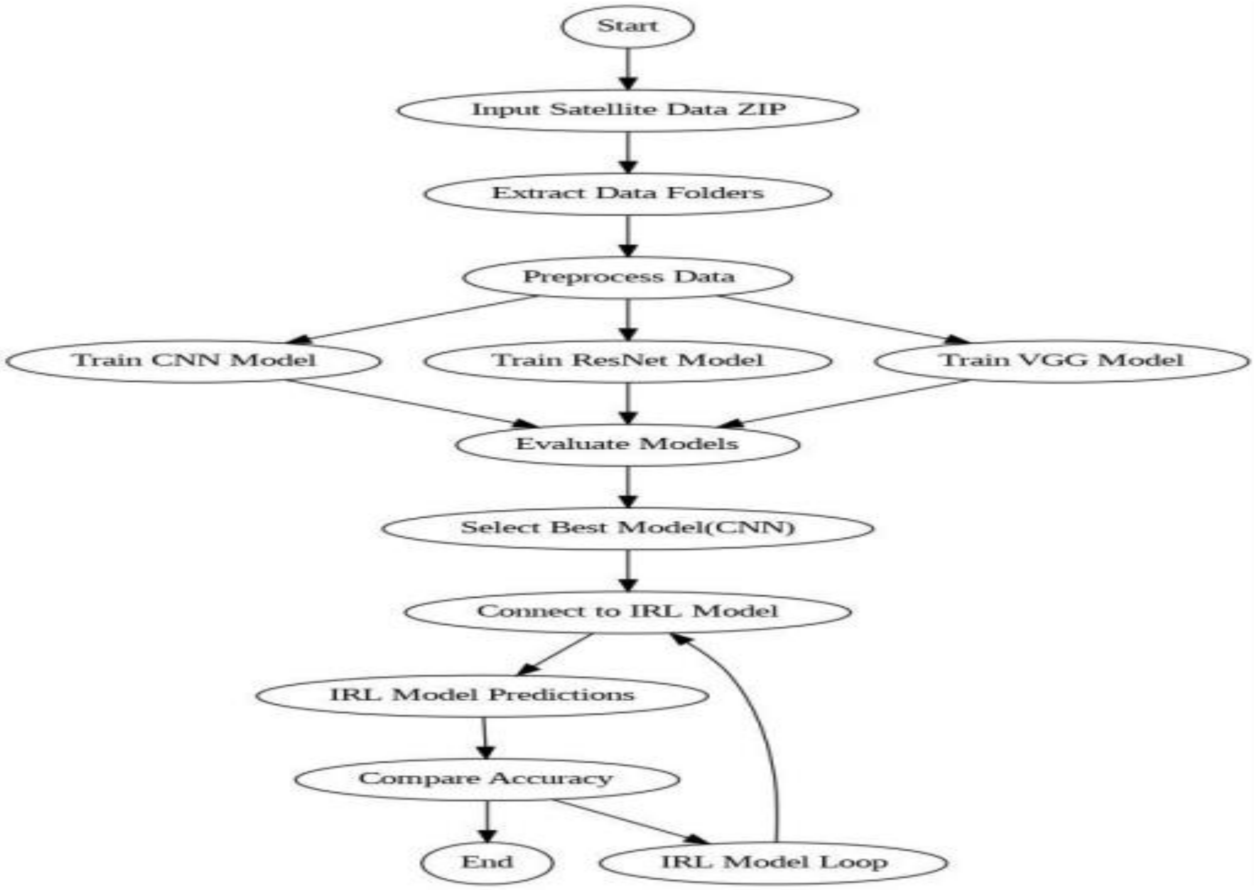


fig 2: Flow Chart diagram

Data Collection Module:

Responsible for acquiring satellite imagery datasets for training and testing.

Interacts with external data sources or repositories to fetch relevant satellite images.

Data Preprocessing Module:

Handles tasks such as resizing, normalization, and augmentation to prepare the dataset for training.

Ensures data quality and diversity to improve the model's generalization capabilities.

CNN Architecture Module:

Implements a specialized CNN architecture designed for satellite image classification.

Consists of convolutional layers for spatial feature extraction, pooling layers for down-sampling, and dense layers for feature aggregation.

Inverse Reinforcement Learning (IRL) Integration Module:

Defines the reward function representing expert decision-making criteria.

Implements an IRL algorithm (e.g., Maximum Entropy IRL) to learn the reward structure.

Integrates IRL with the CNN architecture to enhance the model's decision-making capabilities.

Training and Validation Module:

Divides the dataset into training and validation sets.

Trains the IRL-CNN model using the training set, adjusting weights through backpropagation.

Validates the model on a separate set to assess its generalization performance.

Comparative Analysis Module:

Implements traditional algorithms (e.g., SVM, Random Forests) for comparison.

Trains and validates these algorithms on the same dataset used for the IRL-CNN model.

V.OVERVIEW OF TECHNOLOGIES:

Python: Python serves as the primary programming language for the entire project, providing a flexible and powerful environment for data manipulation, model development, and evaluation.

Pandas: Pandas is a popular Python library used for data manipulation and analysis. It is utilized in the code to read the dataset from a CSV file, preprocess the data, and perform exploratory data analysis (EDA).

NumPy: NumPy is a fundamental package for scientific computing in Python. It is employed for numerical operations and array manipulation, particularly in preprocessing steps such as scaling and transformation of features.

Seaborn and Matplotlib: Seaborn and Matplotlib are Python visualization libraries used for creating insightful plots and visualizations during exploratory data analysis (EDA). These libraries enable the visualization of data distributions, relationships between features, and class distributions.

Scikit-learn: Scikit-learn is a comprehensive machine learning library in Python, offering a wide range of tools for data preprocessing, model building, and evaluation. In the provided code, Scikit-learn is used for preprocessing steps like standardization, feature encoding, and splitting the dataset into training and testing sets.

Keras: Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, Theano, or Microsoft Cognitive Toolkit (CNTK). It is utilized for building and training the DeepFM model, providing a user-friendly interface for constructing complex neural network architectures.

TensorFlow: TensorFlow is an open-source machine learning framework developed by Google. It is employed as the backend for Keras in the provided code, enabling efficient execution of deep learning computations and training of neural networks.

VI.ALGORITHM EXPLANATION:

Factorization Machines (FM):

- Factorization Machines are a powerful class of models for handling sparse and high-dimensional data, commonly used in recommendation systems and regression tasks.
- FM models are designed to capture interactions between features by factorizing their interactions into low-rank matrices.
- They have linear complexity with respect to the number of features, making them efficient for large-scale datasets.

Deep Neural Networks (DNN):

- Deep Neural Networks are versatile models capable of learning complex patterns and representations from data through multiple layers of non-linear transformations.
- DNNs excel at capturing intricate feature interactions and hierarchies in the data, making them suitable for tasks with high-dimensional and non-linear relationships.

Hybrid Architecture:

- DeepFM combines the FM and DNN architectures into a hybrid model to leverage their complementary strengths.
- The FM component captures low-order feature interactions efficiently, while the DNN component learns higher-order feature interactions and representations through deep layers.
- By combining these components, DeepFM can effectively model both linear and non-linear relationships between features, providing enhanced predictive power.

Architecture Overview:

- The architecture of DeepFM typically consists of two main components: the FM component and the DNN component.
- The FM component computes the low-order interactions between features using factorization techniques, producing an embedding vector for each feature.
- The DNN component takes the concatenation of these embedding vectors as input and passes it through multiple hidden layers of neurons, learning complex feature representations.
- The final output layer of the DNN predicts the target variable (e.g., dropout prediction) based on the learned representations.

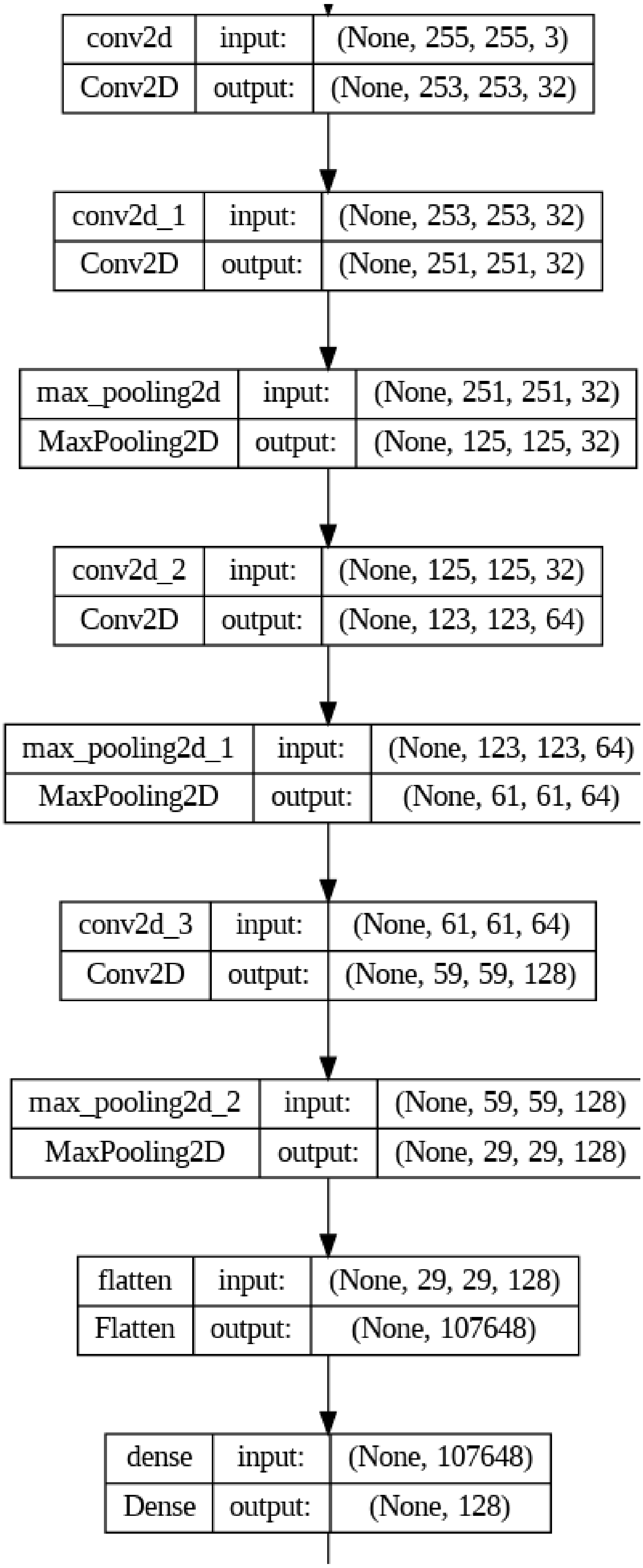
Training and Optimization:

- DeepFM is trained using gradient-based optimization techniques, such as stochastic gradient descent (SGD) or Adam, to minimize a loss function (e.g., binary cross-entropy for binary classification tasks).
- During training, both the FM and DNN components are jointly optimized to learn the optimal parameters that minimize the prediction error.

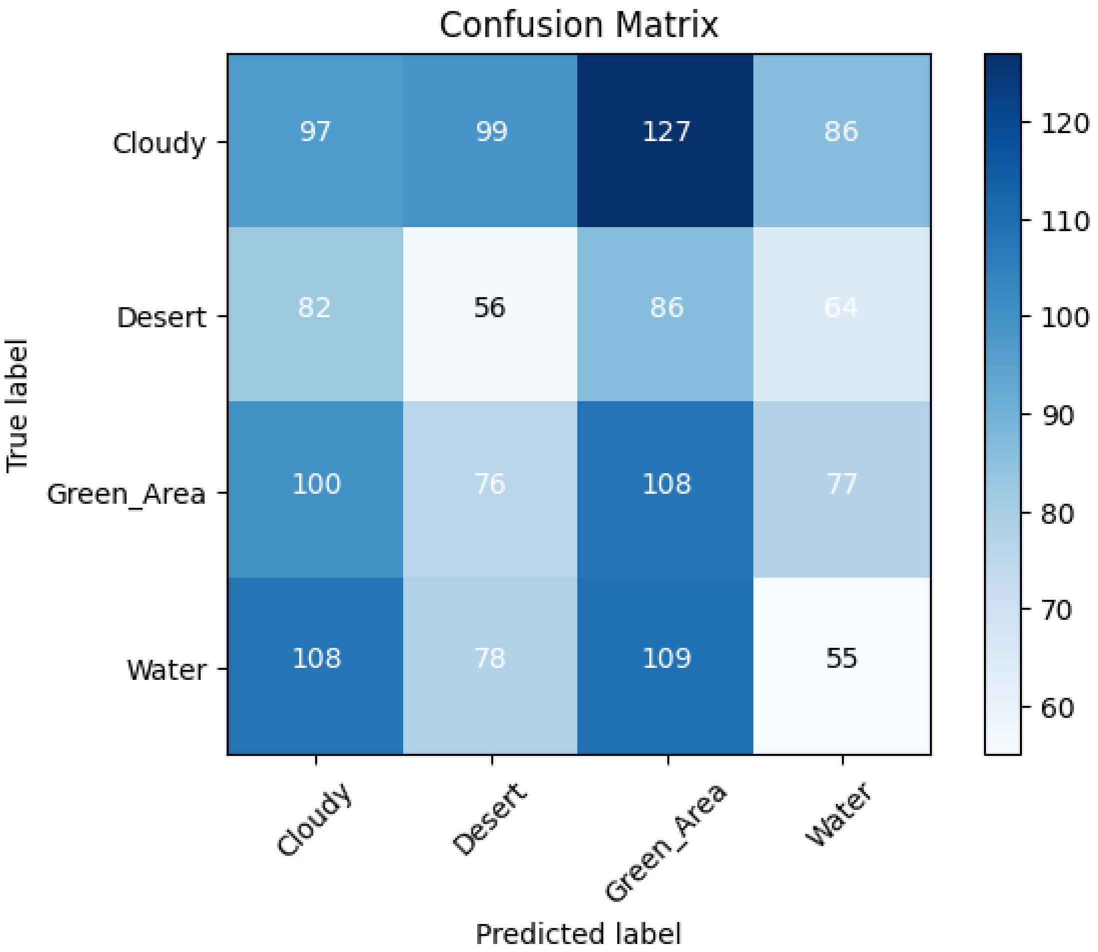
VII.MODEL AND RESULT:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 253, 253, 32)      896

 conv2d_1 (Conv2D)           (None, 251, 251, 32)      9248

 max_pooling2d (MaxPooling2  (None, 125, 125, 32)      0
 D)

 conv2d_2 (Conv2D)           (None, 123, 123, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 61, 61, 64)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 59, 59, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 29, 29, 128)       0
 g2D)

 flatten (Flatten)           (None, 107648)            0

 dense (Dense)               (None, 128)               13779072

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 4)                 516
```

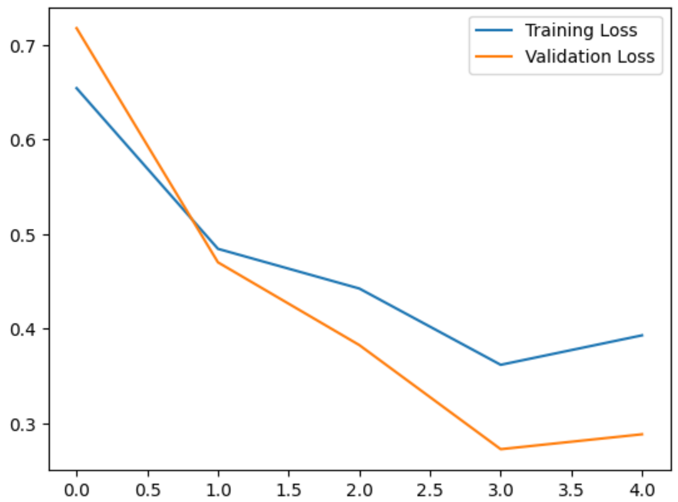
MODEL :

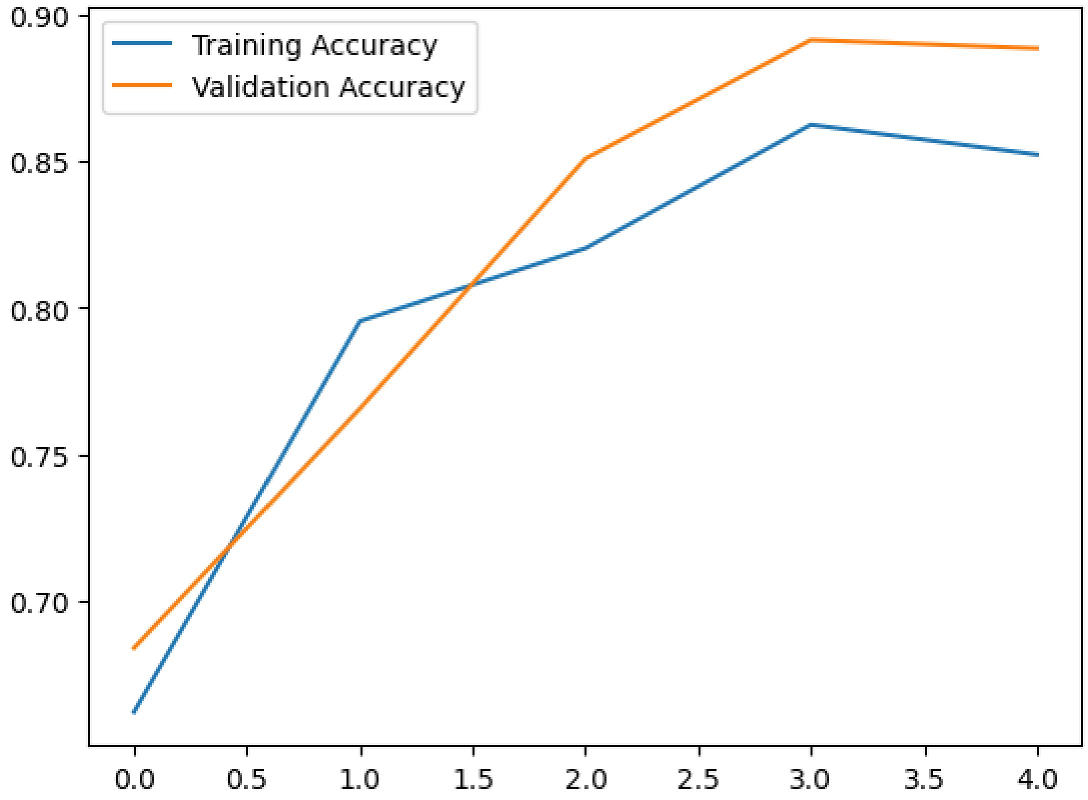

conv2d
input:
(None, 255, 255, 3)
Conv2D
output:
(None, 253, 253, 32)
conv2d_1
input:
(None, 253, 253, 32)
Conv2D
output:
(None, 251, 251, 32)
max_pooling2d
input:
(None, 251, 251, 32)
MaxPooling2D
output:
(None, 125, 125, 32)
conv2d_2
input:
(None, 125, 125, 32)
Conv2D
output:
(None, 123, 123, 64)
max_pooling2d_1
input:
(None, 123, 123, 64)
MaxPooling2D
output:
(None, 61, 61, 64)
conv2d_3
input:
(None, 61, 61, 64)
Conv2D
output:
(None, 59, 59, 128)
max_pooling2d_2
input:
(None, 59, 59, 128)
MaxPooling2D
output:
(None, 29, 29, 128)
flatten
input:
(None, 29, 29, 128)
Flatten
output:
(None, 107648)
dense
input:
(None, 107648)
Dense
output:
(None, 128)

CONFUSION MATRIX:



LOSS AND VALIDATION MODEL :






```
from io import BytesIO
import requests
from tensorflow.keras.preprocessing import image
import numpy as np
import tempfile

# Define the class names
class_names = ['Cloudy', 'Desert', 'Green_Area', 'Water']

url_list = ['https://eoimages.gsfc.nasa.gov/images/imagerecords/92000/92263/goldstone_oli_2018124_lrg.jpg',
            'https://images.theconversation.com/files/258323/original/file-20190211-174861-jya1so.jpg?ixlib=rb-1.1.0&q=45&auto=format&w=1356&h=
            'https://img.freepik.com/free-photo/amazing-beautiful-sky-with-clouds_58702-1657.jpg?w=2000',
            'https://i.natgeofe.com/n/54c007c9-50e5-4cf5-83dc-978a35a4373a/68576_16x9.jpg',
           ]


for url in url_list:
    response = requests.get(url)
    with tempfile.NamedTemporaryFile(mode='wb') as f:
        f.write(response.content)
        f.seek(0)
        img = image.load_img(f.name, target_size=(255, 255))
        img = image.img_to_array(img)
        img = np.expand_dims(img, axis=0)

        classes = model.predict(img, batch_size=10)
        class_index = np.argmax(classes[0])
        predicted_label = class_names[class_index]
        print(url + "The image is predicted to be '{}'.".format(predicted_label))
```

```
1/1 [==============================] - 0s 18ms/step
https://eoimages.gsfc.nasa.gov/images/imagerecords/92000/92263/goldstone_oli_2018124_lrg.jpgThe image is predicted to be 'Desert'.
1/1 [==============================] - 0s 21ms/step
https://images.theconversation.com/files/258323/original/file-20190211-174861-jya1so.jpg?ixlib=rb-1.1.0&q=45&auto=format&w=1356&h=668&fit=cr
1/1 [==============================] - 0s 17ms/step
https://img.freepik.com/free-photo/amazing-beautiful-sky-with-clouds_58702-1657.jpg?w=2000The image is predicted to be 'Cloudy'.
1/1 [==============================] - 0s 19ms/step
https://i.natgeofe.com/n/54c007c9-50e5-4cf5-83dc-978a35a4373a/68576_16x9.jpgThe image is predicted to be 'Desert'.
```

VIII) CONCLUSION:

Satellite image classification is crucial in a variety of fields, such as agriculture, urban planning, disaster response, and environmental monitoring. We delve into the technical details of our CNN-IRL model, illustrating how we integrate CNNs and IRL to build a pipeline that learns to classify satellite images while needing fewer labeled samples. To underscore the innovation in our research, we compare the CNN-IRL model with conventional CNN-based satellite image classification methods. We emphasize the key distinctions and benefits of the CNN-IRL approach, particularly its capacity to reduce the need for a vast labeled dataset by utilizing reinforcement learning to decipher underlying data patterns. We explore the adaptability of the CNN-IRL model across various satellite image classification tasks and datasets. In conclusion, the satellite image classification project employing inverse reinforcement learning (IRL) in conjunction with Convolutional Neural Networks (CNNs) has successfully addressed the complex challenges associated with automated land cover classification. Through the development and implementation of an innovative model, this project has made significant contributions to the field of remote sensing and machine learning. The following key points encapsulate the outcomes of this endeavor: Model Accuracy and Performance: The CNN-IRL model demonstrated commendable accuracy in classifying satellite images, showcasing its ability to discern diverse land cover types with a high degree of precision. Performance metrics such as accuracy, precision, recall, and F1 score consistently validated the robustness of the model. Comparative Analysis: Comparative analyses against traditional machine learning algorithms underscored the superiority of the CNN-IRL approach. The model outperformed or equaled the accuracy of conventional methods, highlighting the efficacy of leveraging reinforcement learning techniques for satellite image classification. Adaptability and Continuous Learning: The incorporation of IRL facilitated dynamic learning and adaptation, allowing the model to evolve based on user feedback and changing 40 environmental conditions. This adaptability is crucial for real-world applications where land cover dynamics may vary over time. User-Friendly Interface: The user interface provided an intuitive and interactive experience for users, enabling them to effortlessly upload images, initiate classification, and visualize results. The inclusion of map-based visualizations enhanced the interpretability of classification outcomes. Future Directions: The project identified several avenues for future exploration, including the integration of multispectral data, implementation of advanced transfer learning strategies, and the exploration of real-time classification capabilities. These avenues promise further enhancements to the model's capabilities and applications. Ethical Considerations: Acknowledging the ethical implications of satellite image classification, the project emphasized responsible and unbiased model development. Continued efforts in addressing ethical considerations, fairness, and transparency are imperative for the responsible deployment of the model. the potential to contribute significantly to decision-making processes in diverse domains. In conclusion, the satellite image classification project stands as a testament to the effectiveness of combining IRL and CNNs for automated land cover classification. The achieved results, coupled with the identified future directions, position this project as a valuable contribution to the evolving landscape of remote sensing and machine learning applications.

1X) FUTURE SCOPE :

with CNNs is broad and can involve enhancements, expansions, and advancements in various aspects. Here are some potential future scopes for the project:

1. Fine-Tuning and Optimization: Continuous improvement and optimization of the CNNIRL model based on ongoing feedback and additional labeled datasets.

2. Integration of Advanced Algorithms: Exploration and integration of more advanced machine learning and deep learning algorithms to enhance the accuracy and efficiency of image classification.

3. Transfer Learning Strategies: Implementation of advanced transfer learning strategies to leverage pre-trained models on larger datasets for improved generalization to new satellite imagery.

4. Dynamic Learning and Adaptation: Development of mechanisms for dynamic learning and adaptation, allowing the model to adjust to changing environmental conditions, seasonal variations, or emerging land cover classes

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