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SATELLITE IMAGE CLASSIFICATION USING DNN

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ABSTRACT

Satellite image classification plays a crucial role in various applications such as land cover mapping, environmental monitoring, urban planning, disaster management, and classification is an important functionality of satellite image analysis. Manual detection of objects in these images is very time consuming. Due to the nature and size of objects and the varied visual features, it becomes challenging to classify in satellite image. The conventional methods for classification involve two stages: identify the regions with object present in the image and classify the objects in the regions. The proposed approach involves a convolution neural network (CNN) model, Mobile net model, designed and trained using labeled datasets of satellite imagery. CNNs are capable of automatically learning hierarchical and abstract features from satellite image data. This reduces the need of manual feature engineering, making the classification process more efficient and effective. This work proposes models, to classify four different datasets of labeled satellite images. Each image should have associated labels indicating the class or category such as cloudy, desert, green area, and water in the images. It also aims to understand and outline briefly the performance characteristics of the considered and emerged as powerful tools for automating this classification process, as they can automatically learn and extract hierarchical features from raw satellite image.

INTRODUCTION

Earth images collected by satellite are called satellite image sources. These images are also referred to as space borne photographs. Satellite companies provide these images for utilization in a variety of application domains. Satellite imaging is gaining importance in many applications like remote surveillance, environmental monitoring, whether forecasting etc. All these applications involve searching objects, event of interest, facilities etc., from the satellite images. In most applications, classification becomes very difficult dealing with satellite images. Satellite images are more challenging as the visual features are extremely hard to track and capture making it all the more difficult.

Towards this end various automated techniques for classification have been proposed and are in the works. . From classical machine learning (ML) to current deep learning, many solutions have been proposed for classification in satellite images. . These methods involve extraction of various features from the images and classifying them using DNN classifiers .A Deep Learning has shown promising results in achieving the classification using DNN. Recently the Deep learning classification methods which have been proposed for automated object detection with high accuracy are able to learn features automatically from the images instead of manual selection of features. Many deep learning models based on deep neural network (DNN) are proposed for classification of objects in satellite images. In this work, a customized deep neural network is proposed to classify objects in satellite images. The model is trained to classify four datasets of cloudy, desert, green area and water in the satellite images.

Deep Neural Networks (DNNs) is a powerful and advanced technique in the field of remote sensing and computer vision. It involves using complex artificial neural networks to automatically categorize satellite images into different classes or categories based on their content. This capability has applications in various domains, including environmental monitoring, urban planning, disaster management, agriculture, and more. Here's an introduction to the process of satellite image classification using DNN .Satellite image classification aims to assign a label or class to each pixel or region in a satellite image this is done by analyzing the visual patterns and features present in the images.

Gather a dataset of labeled satellite images. Each image should have associated labels indicating the class or category like desert, cloudy, water, green area.Designing the architecture of deep neural network like MobileNet, requires specifying the layer configurations and parameters for each network ,model training split your dataset into training, validation, and test sets. This division allows you to train the model on one subset, fine- tune hyper parameters using the validation set, and evaluate its performance on the test set. During training, the model uses pre trained weights for feature extraction and classify them using classifiers: Random forest, KNN .The model's performance on the validation set and Monitor metrics like accuracy, precision, recall, and F1-score at classifying satellite images.

LITERATURE SURVEY

Karen Simonyan, Andrew Zisserman[1] In this paper, they proposed Deep Convolution Networks for Large-Scale Image Recognition Published in arXiv preprint (2014) introduced the VGG network architecture, which is a deep convolution neural network with up to 19 layers. While not directly focused on satellite images, the VGG architecture has been used as a basis for various satellite image classification tasks.

Olga Russakovsky et al [2] In this paper, they proposed Imagenet Large Scale Visual Recognition Published in International Journal of Computer Vision (2015) Although not solely focused on satellite images, this paper discusses the ImageNet Large Scale Visual Recognition Challenge, the development of deep neural networks for image classification. It provides insights into techniques and architectures used for large-scale image classification tasks.

Christian Szegedy et al. [3] In this paper, they proposed Deeper with Convolutions Published in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015) This paper introduced the Inception architecture, also known as GoogLeNet, which uses multiple parallel convolution layers with different filter sizes to capture features at various scales. The ideas from this paper have been applied to satellite image classification. The dataset was used for the purpose of experimentation which contains nearly 7 million labeled pictures of various scenes which is sufficiently **Christian Szegedy et al. [3]** exhaustive dataset to train and test the model to get the desired output. The Inception model networks, thus resulted in average accuracy

Kaiming He et al .[4] In this paper, they proposed Deep Residual Learning for Image Recognition Published in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016) The ReseNet architecture introduced in this paper addresses the vanishing gradient problem in very deep networks by using residual connections. This architecture has been used for satellite image classification due to its ability to train extremely deep networks. ResNet achieved improvements in both training convergence and generalization performance on image classification tasks.

Maher Ibrahim Sameen,et.al.[5] In this paper, they proposed a classification model based on CNN and spectral-spatial feature learning has been proposed for aerial photographs .A convolution neural network (CNN)was developed to classify aerial photographs into seven land cover classes such as building ,grassland ,dense Vegetation, water body, barren land, road, and shadow. The classifier utilized spectral and spatial contents of the data to maximize the accuracy of classification process .CNN was trained from scratch with manually created grouped truth samples .There are several methods and algorithms that have been adopted to efficiently classify a very high resolution aerial photo and produce accurate land cover maps .The CNN model acts as a feature extractor ,and a classifier could be trained end –to-end training samples .The network architecture can effectively handle the inter- and inter class complexity inside the scene .The best model achieved OA=0.973,AA=0.965and K=0.967 outperforming is the traditional CNN model by ~4% in all the accuracy indicators .The short training time confirmed the robustness of the proposed model for small and medium scale remote sensing dataset

Lihua Ye, et.al. [6] In this paper, they proposed a parallel multi-stage features fusion of deep convolution neural networks for aerial scene classification. The architecture formed by a low, middle, and high deep convolution neural network (DCNN) sub-model. PMS model automatically learns representative and discriminative hierarchical features, which include three 512 dimension vectors, respectively, and the final representative feature created by linear connection. PMS model describes a robust feature of aerial image through three stages feature. Unlike previous methods, we only use transfer learning and deep learning methods to obtain more discriminative features from scene images while improving performance. The obtaining average classification accuracies of 98.81% and 95.56%, respectively, on UC Merced (UCM) and aerial image dataset (AID) benchmark datasets.

Jie Chen, et.al [7] In this paper, they proposed remote sensing image scene classification is a fundamental but challenging task in understanding remote sensing images. Recently, deep learning-based methods, especially convolution neural network-based (CNN-based) methods have shown enormous potential to understand remote sensing images. CNN based methods meet with success by utilizing features learned from data rather than features designed manually. The feature learning procedure of CNN largely depends on the architecture of CNN.

uhammet Ali Dede, et.al. [8] In this paper, they proposed on aerial scene classification through deep network ensembles, it is well known in the machine teaching community that the ensembles of neural networks outperform the respective individual networks; hence recent work on aerial scene classification has been trending toward various network fusion strategies. However, training multiple deep networks can be computationally expensive. "Snapshot ensembling" has recently appeared as an alternative and claims to provide the performance of network ensembles at the cost of a single network's training.

Xiaoxiang Zhu and Devis Tuia.[9] In this paper, they proposed on Deep Learning for Remote Sensing Image Analysis published in 2018.The paper starts by introducing the fundamental concepts of deep learning, including neural networks and convolution neural networks (CNNs). It explains how these techniques have transformed the field of remote sensing and satellite image analysis. Challenges may include handling large volumes of data, dealing with different sensors, and achieving accurate classification in complex environments.

Sidra Ijaz and Saeed Anwar.[10] In this paper, they proposed on Convolution Neural Networks for Remote Sensing Image Analysis published in 2017. **Provides in-depth exploration of** the application of Convolution Neural Networks (CNNs) in the field of remote sensing image analysis, which includes satellite image classification. It explains the architecture of CNNs, including convolution layers, pooling layers, and fully connected layers. CNNs are adapted to remote sensing image analysis.

METHODOLOGY

PROPOSED SYSTEM

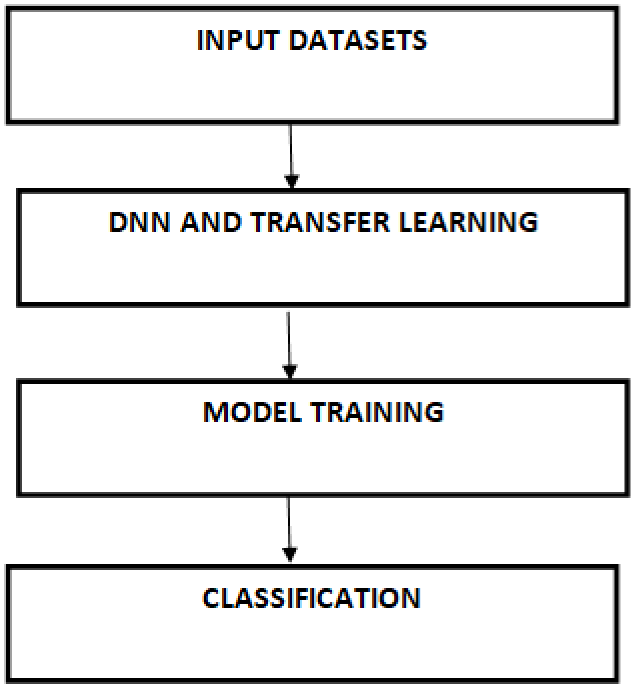


Fig1 Proposed System

Deep learning and Machine learning can be used for environmental monitoring, whether forecasting and prediction of various land cover type. The main goal of this paper is to provide a tool for accurate and automated analysis of satellite imagery across land cover type applications. This in turn will help to introduce an advanced framework of deep learning and Machine learning to classify satellite images effectively.

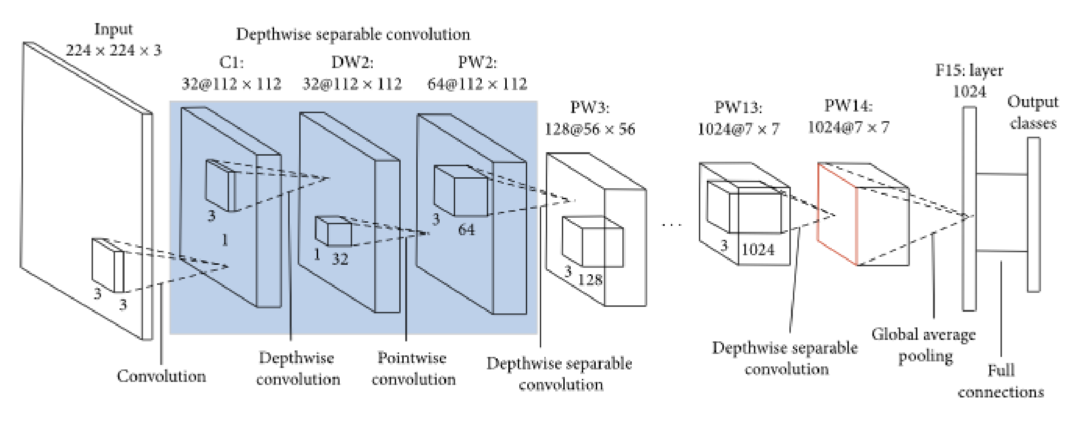
The proposed task is to develop a robust and accurate deep neural network (DNN) model for satellite image classification. The records in the dataset are divided into training set and test sets. The features that are used to classify the image extracted by using pre trained CNN models: MobileNet, and compare the result among them .The MobileNet model achieve a promising result .Models designed and trained using labeled datasets of satellite imagery**.** The model comprises multiple layers, including convolution layers for fully connected layers for classification. The project involved analysis of the satellite image classification dataset with proper data processing. The classification with model were trained and tested with maximum scores as follows:

1. Random forest classifier

2. K-Nearest Neighbors classifier

MOBILENET ARCHITECTURE

MobileNet is a deep convolution neural network architecture designed for efficient and lightweight image classification. It's characterized by its depthwise separable convolutions, which significantly reduce the number of parameters and computation while maintaining good accuracy.



ALGORITHM

Random Forest

Random Forest is a supervised machine learning algorithm. This technique can be used for both regression and classification tasks but generally performs better in classification tasks. As the name suggests, Random Forest technique considers multiple decision trees before giving an output. So, it is basically an ensemble of decision trees. This technique is based on the belief that more number of trees would converge to the right decision. For classification, it uses a voting system and then decides the class whereas in regression it takes the mean of the entire outputs o the decision trees. It works well with large datasets with high.

KNN

K-nearest neighbors (KNN) algorithm is a type of supervised ML algorithm which can be used for both classification as well as regression predictive problems. However, it is mainly used for classification predictive problems in industry. The following two properties would define KNN well

Lazy learning algorithm − KNN is a lazy learning algorithm because it does not have a specialized training phase and uses all the data for training while classification.

Non-parametric learning algorithm − KNN is also a non-parametric learning algorithm• because it doesn't assume anything about the underlying data.

The k-nearest neighbor's algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another.

SYSTEM ARCHITECTURE

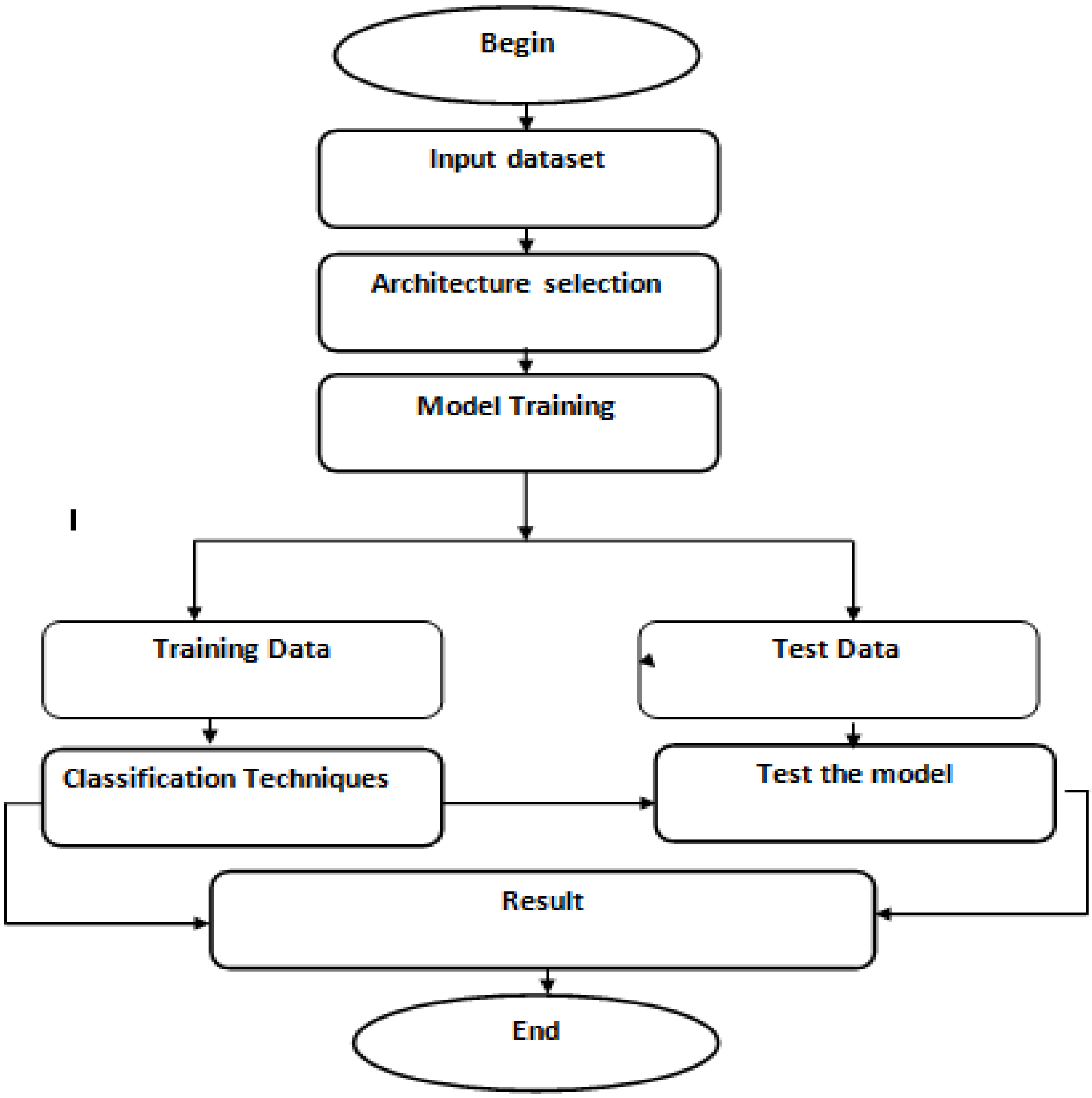


Fig.2.Architecture of proposed method

Input Dataset

Gather a labeled dataset of satellite images these images should have associated ground truth labels indicating the land cover type.

Image Preprocessing

Images are susceptible to various types of noises to deal with noises pre-processing techniques are used. Following are the pre-processing techniques we have applied to our dataset

Image Resize

To feed into the proposed architecture images are downsized to 128x128.Format of images are kept in JPEG. Downsizing size helped us in reducing the training and testing time significantly

Select Architecture

Choose a deep learning architecture suitable for image classification. Common choices include Convolution Neural Networks (CNNs), which are well-suited for image data. We used a pre-trained CNN models like, MobileNet .

Model Training

Implement data loaders to efficiently load and preprocess your satellite images and labels in batches during training: Select an optimizer like Adam or SGD for updating model weights train the model on your training dataset using the prepared data loaders.

Sure, let's break down the satellite image classification process into more detailed steps, including examples of each component:

Training Data and Testing Data

Split your dataset into three subsets: training, validation, and test sets. Common splits include 70% for training, 15% for validation, and 15% for testing .Adjust these percentages based on the size of your dataset.

Classification Techniques

In this context, the primary classification technique is machine learning using CNNs. However, we can also use techniques such as Random Forests, K-Nearest Neighbors (KNN)

Test the Model

Use the testing dataset to evaluate the model's performance using various evaluation metrics: Accuracy, Precision, Recall, F1-Score and Confusion Matrix.

Performance measure

Confusion matrix-based performance metrics are used for evaluating the significant improvement of the proposed satellite image classification model over the competitive supervised Aerial Scene classification models. These metrics include accuracy, precision, recall and F1-score, and negative predictive value.

Accuracy

We implemented and displayed Classification Metrics (precision, recall, F1-score, support), along with their micro and macro average and weighted and samples average. Precision is a good measure when classification accuracy is not a good indicator of your model performance when your class distribution is imbalanced. Recall is defined as the fraction of samples from a class that are correctly predicted by the model. One popular metric which combines precision and recall is called F1-score. Support is the number of samples of the true response that lie in that class.

Precision

Precision is the ratio of the correctly identified positive cases to all the predicted positive cases, i.e. the correctly and the incorrectly predicted cases. Precision is the fraction of retrieved documents that are relevant to the query

The formula:

$$\text{PRECISION} = \frac{\text{TRUE POSITIVE}}{\text{(TRUE POSITIVE+FALSE POSITIVE)}}$$

Recall

Recall, also known as sensitivity, is the ratio of correctly identified positive cases to all the actual cases, which is the sum of “False Negatives” and “True positives”.

The formula:

$$\text{RECALL} = \frac{\text{TRUE POSITIVE}}{\text{(TRUE POSITIVE+FALSE NEAGITIVE)}}$$

F1- score

F1 score represents the model score as a function of precision and recall score. F-score is a machine learning model performance metric that gives equal weight to both the Precision and Recall for measuring its performance in terms of accuracy; making it an alternative to Accuracy metrics (it doesn't require us to know the total number of observations

$$\text{F1-score} = \frac{2*(\text{PRECISION} + \text{RECALL})}{(\text{PRECISION} + \text{RECALL})}$$

Results

The trained model achieves accuracy on the testing dataset, with high precision and recall for each land cover class. Visualize the results, including class-wise accuracy, and inspect misclassified images to identify potential areas for improvement.The overall accuracy for satellite image classification is a common metric used to assess the performance of a classification model applied to satellite imagery. It measures the proportion of correctly classified pixels or objects in the entire dataset. However, it's important to note that while overall accuracy is a straightforward and widely used metric.

CONCLUSION

The proposed approach involves a MobileNet model is capable of automatically learning hierarchical and abstract features from satellite image data. This reduces the need of manual feature engineering, making the classification process more efficient and effective. The model comprises multiple layers, including convolution layers for fully connected layers for classification. Architectures can be adapted to different types of satellite image classification tasks. The same framework can used for various application, such as land cover classification, whether forecasting, Environment monitoring. They can learn complex patterns and features in the data, leading to higher accuracy.

The implementation for automatically classifying satellite imagery using deep neural network (DNN).The satellite imagery is a challenging problem so, we introduced the custom DNN model for classification of Satellite images.

The performance of the proposed solution was tested for 4 different datasets that is cloudy, desert, green area, Water The method was able to achieve a best accuracy. The volume of training image used in this work is small. The ability of deep neural network (DNN) is to automatically learn and extract relevant features from the input imagery this is been a key factor in success.

FUTURE ENHANCEMENTS

1. Improved Generalization to Unseen Data: Enhancing the ability of DNN models to generalize well to unseen geographic regions, seasons, and atmospheric conditions is a key area of research.
2. Multisource and Multimodal Data Fusion**:** Integrating data from multiple sources can improve classification accuracy and provide richer contextual information
3. Adversarial Robustness**:** Developing DNN models that are robust against adversarial attacks is crucial for real-world applications.
4. Real-Time and On-Device Processing**:** Developing DNN architectures that can provide real-time or near-real-time classification on low-power devices will be important for applications like remote sensing on drones or autonomous vehicles.

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