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An Innovative Method for Categorizing Satellite Images via Enhanced Deep Convolutional Neural Network

Sahana S H [1*],Dr Raghavendra SP [2]
[1*]Student, [2*]Assistant Professor, Department of Computer Applications
JNN College of Engineering, Shimogga
sahanamadakari24@gmail.com, raghusp@gmail.com

Abstract

Satellite image categorization plays a optimal role in various scenarios includes natural disaster response, earth monitoring, prevention of hazardous events and analysis of terrestrial biodiversity. CNN algorithms employed on deep learning were exploited to classify orbital images into respective categorize. In addition to this study categorize satellite photos but it can also categorize obvious classes and recognizing the specific traits of those cataloging categories. The main issue with satellite photography is that different satellite images may have different characteristics, which makes space probe image categorization challenging. Another issue is that the majority of safe light images include signal purification over-the-air imagery noise structure are estimated using the CNN mode. The proposed system involves the convolution neural network and it is implemented in python through the tenser flow and keras libraries. In this article carried out ResNet-50 model, which was able to enrich the classification feasibility more than 96% accuracy.
Keywords: *Convolutional neural network**,** Remote sensing, Image Processing, Deep Learning*

1. Introduction

Geographical image classification a curious routine in remote supervision. It involving the cataloging of pixels in satellite images into green area, cloudy and desert. The classification undergo through the deep learning technique, it involves various application to get the accurate outcome. CNNs use a unique regularization technique that takes advantage of the hierarchical nature of data to piece together increasingly complicated patterns from smaller simpler patterns that are contained in its filters. They function at the less complicated and connected end of the spectrum they offer the probability of each class being classified. CNNs are thought to be the optimal methodology for this study though because of the much smaller dataset that was employed in the current inquiry numerous performance indicators were exploited to evaluate different supervised algorithms.

2. Related Work

Aaqib Mehran et al., (2022) [1] author's explores the challenges in the satellite image sensing in the daily activities. They mainly focus on the maritime technologies which indeed to detect the ships. They proposed the framework convolutional neural network algorithm is inception-ResNet which is the pre-trained model. Through this conceptual model provide the success rate of accurate found greater than 99%.

Abubakar Salihu Abba et al., (2020) [2] author's explores a new categorization technique for satellite image categorization. This method is also known as Tranfer Learning-Convolutional Neural Network(TL-CNN). This method includes the layers such as Convolutional layers, Rectified linear unit layer, Max pool layer and main categorization. It is based on the model type of ResNet using Aerial Image Dataset(AID). Here Tl-CNN has significant improve of the classifying accuracy of 99.99% and that technique enhance the categorization accuracy.

Mark Pritt et al., (2017) [3] author's focus on the deep learning systems for which categorization facilities and taken IARPA Functional Map of World(fMoW) dataset which having 63 different classes. They have implemented the transfer learning which follows common practices and for data augmentation they increased the size of dataset. They found that one epoch is sufficient for better yield of training. They got the accuracy of 83% and f1 score is 0.797 and their system yields a TopCoder score of 7765,663. They have taken 2nd place in fMoW TopCoder competition and they classifiers the 15 classes with efficient of 95%.

M. P. Vaishnnave et al., (2019) [4] author's explores the remarkable attention in the sorting of satellite imagery and compressive survey of progress on dataset and the models attainable for image classification. They furnished the compressive analysis of AexNet, caffeNet, GoogleNet, VGNet-16, Inception-v3, ResNet-50. By the analysis of this model type, exactness and accuracy for the evaluating the sateliite image reorganization.

Mayar A. Shafaey et al., (2019) [5] author's focus on the geospatial images where categorization on the technique such as unsupervised and supervised feature and also object based methods they have used deep learning convolutional neural network method on the uc-merceed dataset which implements the AlexNet architecture on this dataset deep learning methods are offer facet representation for the satellite image categorization they have parallelly computed and GPUs for execution time 100x that the several compotators and their experiment executed in time which does not exceeding 14s to classifying the image which one out of 2100 images.

Ramez Shendy et al., (2024) [6] they have addressed the challenges of deploying deep machine learning which rooted on the dataset OPS-SAT. They projected the methodologies which optimize the image classification through data-centric techniques which build upon the convolutional architecture. They have maintained the models framework unchanged of data variables, pre-training and transmit learning model. They have adopted the FSIC(few-shot image categorization) which generate efficient overcome for the challenges.

Roshni Rajendran et all., (2020)[7] authors explores the brief survey of the CNN techniques. where they describe the pivots functions of the layers, filters and dectecting specific traits and brief history of the cnn layer with exploited analysis. They mainly explores the function of layers.

Rukhsar Yousaf et al., (2023) [8] author's focus on the quick analysis and precise analysis of classification on satellite imagery which is based on the deep convolutional neuron network, SnapResNet which having the fully connected layers. They have applied the satellite images which was captured by Himawari satellite they have choosen ResNet architecture. Through proposed SnapResNet images classification with comparative methods with this model perform an accuracy of 97.25%.

Samabia Tehsin et al., (2023) [9] author's focus on the remote geospatial imaging interpretation technique to classify the satellite photographs major into four areas such as sea, greenery, cloudy and deserts. This model gives a efficient precision they have implemented efficient architecture for satellite snapshots categorization. It is the novel approach to increase the accuracy and also decrease the cost of training the model. They have taken the dataset RSI-CB256 for this work. This proposed methodology yields 99.64% accuracy.

Sharada Prasanna Mohanty et all., (2020) [10] author's focuses on the CNN bosting algorithms, filters and random fields. They have gathered SpaceNet dataset they represent automated image annotation and adapted the U-Net and Mask-RCNN rooted approhes. The vital application applied for building maps. They provided the 1-epoch with 20 cycle and they achived precise outcome as AP=0.937 and 0.959.

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3. Proposed methodology

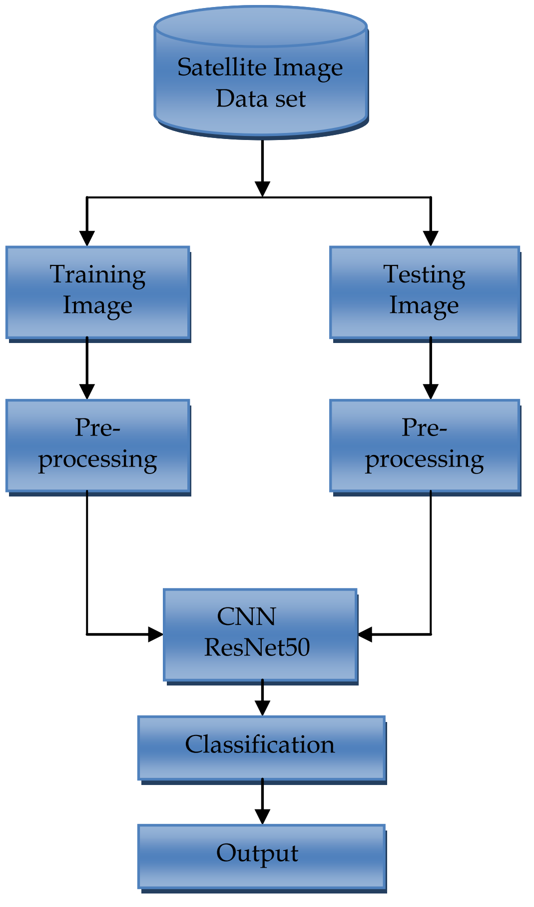

Figure 1: Block diagram of Proposed methodology

a. Data description:

The data collection used for the work is excusively downloaded from the kaagle.com which are labelled. From that dataset images are taken to undergo process, which are assets to three classes such as cloudy, green area and desert. Out of 100% images, 80% files are taken for training and. Here bellow figure 3.1.1 shows some of images which are some of the samples of dataset.

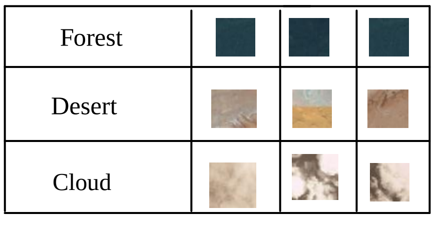

Figure 2: Samples of image dataset

b. Data preprocessing:

The dataset satellite images are resized according to standard size of 256 x 256 pixels and batch size are set as 32. The seed level of coding is 3(RGB image).

$$X \in R^{h \times w \times c} \text{....(1)}$$

In eqaution 1, indicates h stands for height of the image, w for width and c for number of channels(RGB).

c. Working principle

The proposed methodology adopted the CNN algorithm. The CNN algorithm consists of pre-trained model names as resnet-50 and used the sequential model type and following layers are undertaken was activation layer, flatten layer, and dense layer. In activation layer, ReLu and Softmax fuctions are undertaken which introduce the non-linearity and enabling the multi-class classification respectively. The model compillined with an adam optimizer and then trained with the training dataset through 10 epoch and validation to get the accuracy and precison.

Applying Covolutional operation:

$$Z = \mathrm{Conv}(X, W) + b \ldots(2)$$

In above equation 2 represents the convolutional operation, where W stands for weights and b for bias.

d. Model selection

ResNet-50 is a deep learning model extensively used for assorted snapshot categorization missions embracing satellite image categorization. Utilizing a sequential model type that incorporates adaptive, flatten and dense layers can significantly enhance ResNet-50 accomplishment. The evaluation metrics for

- For activation function(Relu):

$$A = ReLU(Z) \ldots(3)$$

- For pooling(Max pooling):

$$P = \text{MaxPool}(A)\ldots.(4)$$

In this configuration, ResNet as a 50-layer of neural network is employed for its robust feature extraction capabilities. An adaptive layer first adjusts the input data to a format compatible with the network. Following the convolutional layers of resnet50, a flatten layer transforms the 2D matrix of features into a 1D vector, preparing it for the fully integrated dense layers.

- Flatten the pooled feature map:

$$F = Flatten(P)\ldots(5)$$

- For fully connected layer:

$$Z_{fc=}W_{fc} \cdot F + B_{fc}\ldots(6)$$

- For activation function(ReLu)

$$A_{fc} = ReLu(Z_{fc})\ldots.(7)$$

These dense layers regularly activated by functions like Relu and softmax, facilitate the final labelling of satellite images into distinct sections. By leveraging the strengths of ResNet50 alongside adaptive, flatten and dense layers. This approach enhances both the precision and efficiency of image sorting missions. The adam optimizer is a popular choice for training models due to efficient handling of sparse gradients on noisy data. We have sets the learing rate for the optima to 0.001, employ sparse categorical cross entropy.

- Output layer:

$$\hat{Y} = Softmax(Z_{fc})\ldots.(8)$$

- For Computing the Cross-entropy loss:

$$L = \frac{-1}{m}\sum_{i=1}^{m}\left[Y_i \log(\hat{Y}_i) + (1 - Y_i)\log(1 - Y_i)\right]\ldots.(9)$$

In above equation 9 indicates the cross entropy loss, where m represents the number of samples, Y represents the true label and $\hat{Y}$ represents the predicted probability.
The configuration of parameters in this methodology are:

1. Overall count of parameters: 24644495(94.01 MB)
2. Total learnable parameters: 1056783(4.03 MB)
3. Total Non-learnable parameters : 23587712(89.98 MB)

4. Results and Discussion

This project presented the CNN model using ResNet-50 wirh the accuracy of 97%.Over here training data taken as 80% and testing data taken as 20%.

4.1 Evaluation Metrics:
Accuracy measures the overall correctness of the systsem prediction. To caluclate the process of acurracy, precision, recall(sensitivity) and F1 score are follows

- Accuracy

$$\frac{CP+CN}{CP+CN+FP+FN} = \frac{970+950}{970+950+30+50} = 0.96\ \ldots.(10)$$

In above equation 10, the formula of accuracy,
CP - Correctly predicted positive cases- 970
CN - Correctly predicted negative cases.- 950
FN - Incorrectly predicted negative cases- 50
FP - Incorrectly predicted positive case- 30.

- $Precision = \frac{CP}{CP+FP} = 0.97$…...(11)

- $Recall = \frac{CP}{CP+FN} = 0.951....(12)$
- $F1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall} = 0.96....(13)$

The above formula measures the overall correctness of the model, accuracy of positive predictions as in equation 11, measures the ability to specify all relevent instances and F1 score as equation 13, that balances the precision and sensitivity of harmonic mean. These metrics rate the performance of a satellite image classification model.

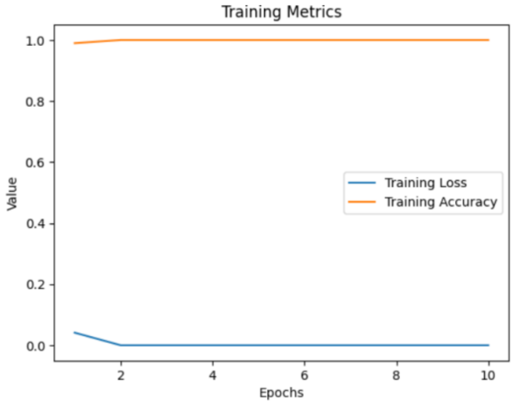

Figure 3: Snapshot of Training accuracy.

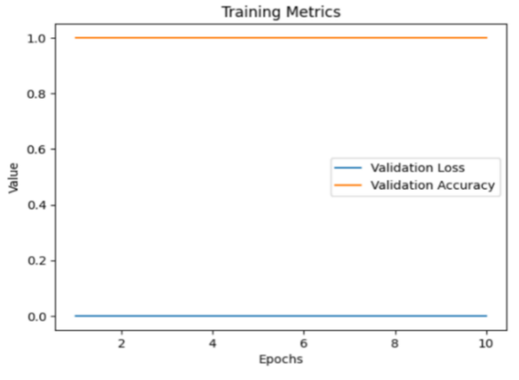

Figure 4: Snapshot of Validation accuracy.

The above figure 4.1 illustrate the training losses and accuracy for every epoch, providing a visual presentation of the framework performances during training and figure 4.2 illustrate the validation accuracy and losses .These lines shows how the model's demonstration on the evaluation data changes for every epoch. By plotting the changes in both training and evaluation metrics for every epoch. It can compare the models efficiency. It improvements in training and evaluation metrics behind to deteriorate while training metrics continue to improve this could indicate overfitting.

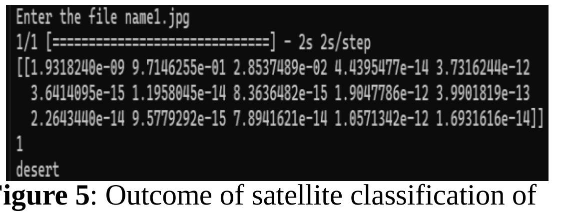

Figure 5: Outcome of satellite classification of image with probability ratio.

Here, the above figure 4.3 represents that the given input as image(desert), where it can classify through the highest predicted values with highest similarities through this probability ratio. Which having maximum value will be predicted.

5. Conclusion

In this project, the critique of the Resnet50 model for satellite image categorization has proven to be accuracy of 96%. The model ability to categorizing well to new data, combined with its high accuracy, makes it a valuable tool for various implementations in disaster response, urban planning, environmental monitoring, and agriculture. Future improvements focusing on data augmentation, class balancing, and ensemble methods can further enhance the model's effectiveness, broadening its applicability and impact.

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