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A High-Efficiency Satellite Image Classification Method for Real-Time Application Using Augmented Incremental Transfer Learning

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Abstract*: Researchers have put forth a range of models for processing satellite images, each with distinct data formats and processing requirements. One limitation arises from variations in the forms of modules, such as the image capturing and feature extraction modules, impacting accuracy and scalability in real-time scenarios. This passage introduces and explores a pioneering very competent temporal engine crafted specifically for classification of real-time satellite images. The proposed approach utilizes augmented incremental transfer learning, aiming to mitigate the limitations associated with diverse processing requirements. This approach involves capturing real-time satellite data through Google's Earth Engine and subsequently processing it using a Convolutional Neural Network (CNN) based on transfer learning. The CNN employs backscatter coefficient analysis, utilizing coefficients derived from Precision Image's average intensity value across a distributed target. By integrating incremental learning and CNN for classification, the model achieves an impressive average accuracy of 98.06% in detecting crop type and severity of damage. Comparative analysis with state-of-the-art approaches reveals the superiority of the proposed model. It outperforms existing models by 5% in accuracy, showcasing its efficacy in satellite image processing and classification.*

Keywords: Earth, Satellite, crop, type, damage, classification, deep learning, incremental, transfer, accuracy, precision, recall

I. INTRODUCTION

In satellite image processing multidomainare involves like image capturing, segmentation, denoising, feature reduction, feature extraction, post-processing tasks, and classification. Researchers propose a variety of satellite image processing architecture, each with diverse process and data necessities. For example, the image acquisition module may receive images in the form of layered, while the feature extraction module may require data in 3D or 2D form. In addition, accuracy and scalability of this model is limited in the real time scenarios due to variation in the dataset parameters and internal process parameters. The motivation behind this research is to develop a novel method which will be able to overcome these issues.

Multiple image processing jobs that should be able to function with various bands of image data must be designed in order to classify satellite images. These include feature extraction, feature selection, classification, band-based, band fusion, pre-processing, post processing, segmentation, and feature-based pre-processing. Figure 1 show the typical satellite image processing model.

This involves stacking and sequencing images from several bands in order to extract patches and estimate sequences. In order to extract a large number of features, the extracted patches are sent to a windowing layer, which separates them into smaller components. This sets feature is categorised using a deep learning (DL) model that creates the first clustered map by combining several convolutional neural networks (CNNs). A post-processing layer receives this initial map and helps create a refined map that can help identify the various components of the region being tested. These elements may include urban cover, crop type, crop cover, water cover, and land cover.

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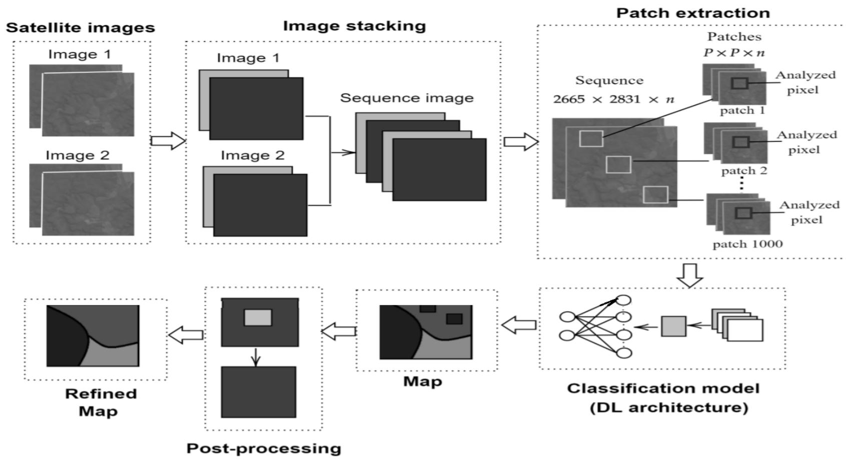

Figure 1 A Typical Satellite Image Processing Model

Numerous classification methods and architectures are suggested by researchers [1, 2, 3], each with a unique applicability, accuracy, classification delay, complexity, and other characteristics. We have proposed the concept of far-filed image classification for real-time application employing enhanced incremental transfer learning for crop in order to increase this performance. This model's performance is assessed in terms of latency, precision, area under the curve (AUC), recall, and accuracy and it is contrasted with other recent advanced techniques. At the conclusion, we discussed the findings about our model and offered similar suggestions for enhancing performance.

II. LITERATURE REVIEW

There are many methods for categorizing satellite images, and the most popular ones are designed for a specific purpose. The most well-known categories of models centre on certain types of satellite pictures. The findings in study found [4,5,6] that Multispectral and Multangle 3D CNN classification is beneficial for the impervious surface analysis, classification of urban images,and a study of multitemporal images using the MDFN. To make this model more scalable, the study presented in [7] proposes creating a CNN model that can be used in remote sensing applications.

The models suggested in [8,9,10] are designed for different purposes - land cover classification by using Features Extraction and Classification Algorithms, comprehensive dominant forest species classification by using Neural-Based Hierarchical Approach, and semi-supervised adversarial deep Network (SSADN) for Segmentation of Satellite Images, but they were inspired by this technique.Researchers have proposed models that are very similar to each other. These methods seek to reduce duplication to increase classification performance, which is scalable to many applications.A few of these methods include TPTSC [12], using DL to categorize land use and land cover [11], ship detection using artificial training datasets [13], and rice paddy detection using deep learning [14].Each of these methods is discussed in detail, including their use cases and common pitfalls. While anyone of these algorithms can be utilised in large-scale classification applications, they must be validated further. [15,] provides the evidence behind the use of support vector machines (SVMs), attention-based CNN (ACNN), Graph Models with deep learning and for the processing of polarimetric data.These topics are intended to improve system performance. To predict image changes while maintaining a low error rate, these models combine various types of images and eliminate redundant features. To provide enough time for a model or two to accumulate data and get feedback, these models need a lot of delays.

2.1 Proposed Model

It is very clear from the literature review that the model reported till date are very much application specific with their specific data set requirement and algorithm. Also, the model developed can provide a specific and accurate result for a specific condition but will give tremendous bad result for different data set. This put limit on their use for general purpose application at the same time a single model cannot be implemented for all scenario. In this thesis we have suggested a satellite image classification model to overcome this limitation of existing model. The suggested model use augmented incremental transfer learning which make the model more efficient and applicable for real-time problem.

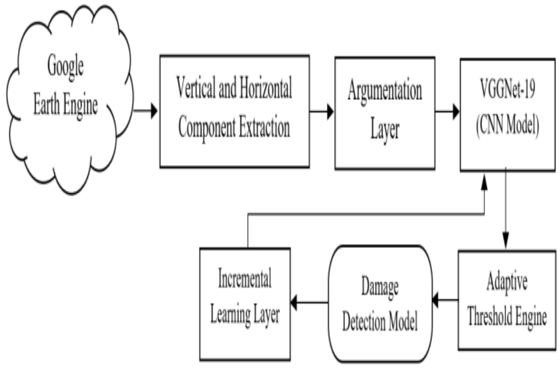

Figure 2. Flow of the Proposed Model

As we have implemented the CNN architecture with incremental learning it helps in continuously improving classification accuracy. Figure 2 show the overall flow of the proposed model. In the suggested model images are downloaded from Google Earth Engine from which the VV & VH components are extracted and then augmented via reshaping, resizing, rescaling, and sheering operations. After that VGGNet-19 architecture is implemented for crop image classification. The input to the crop damage detection model is images which are tag with crop type. the main function of the block is to detect the damage severity by using adaptive threshold engine. A block of the incremental learning layer is used to confirm the threshold engine's results. The correlation-based matching & hyperparameter tuning methods, aid in fine-tuning the VGGNet model.

The data was collected in and around the Amravati area (77.7523, 20.9320) from 2015 to 2021, and analysed using the suggested model. Google Earth engine is the best tool in the hand of researcher now a days which will help in accessing the real-time satellite images with different Temple zone, we have collected the images from this engine for our work. These sources were interpolated via multiple location-based data access, wherein current area was segregated into different sub-regions, and each region was processed via different transmitter receiver polarization.

Following process is adopted to extract the region from Google Earth engine longitude and latitude

Provide the targeted area in the form of $Lat_{target}, Long_{target}$

Download the Extract COPERNICUS surface temperature collections and MODIS land cover collection images for this target.

Fine out the VH and VV component via equations 1 and 2 as follows,

$$VV_i = \frac{\sum_{i=1}^{NBands} B_i - B_{RGB}}{\sum_{i=1}^{NBands} B_i + B_{RGB}} \dots (1)$$

$$HV_i = \frac{\sum_{i=1}^{NBands} G_i - G_{RGB}}{\sum_{i=1}^{NBands} G_i + G_{RGB}} \dots (2)$$

Where, G & B represents their green & blue components, G_{RGB}&B_{RGB} represents green & blue components of RGB band, and $NBands$ represents number of bands extracted from Google Earth Engine.

VV and HV images are formed for current location after these values are extracted for each pixel.

To extract a greater number of images from the current location the current latitude and longitude are modified via equation 3,,

$$New_{lat} = Lat_{target} \pm 0.1, New_{long} = Long_{target} \pm 0.1 \dots (3)$$

VV and VH images are extracted to form the initial training set for each of these latitude and longitude positions.

Different crop kinds and damage percentages are recorded with each image in the training set, which is manually annotated. For the purpose of developing training sets accurately, this data was taken from the Indian Meteorological Dataset (https://mausam.imd.gov.in/), and it may be scaled to any global geographic region. There aren't enough images in the gathered dataset to allow for effective CNN training. An augmentation layer is activated to fix this problem by resizing, resizing, sheering, and reshaping each of the input images.

For each input image, these augmented images are merged to produce 292 images, which are then provided to the VGGNet19 model. The retrieved images are scaled down to 128x128 for the initial convolution operations that help

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with the extraction of enhanced features. Multiple layers of convolution with various stride sizes, padding sizes and window sizes, are employed to aid in large-scale feature extraction. The extraction of over 1 million features from each augmented image set is made possible by the use of stride sizes from 3x3 to 5x5, padding sizes from 3x3 to 5x5 and window sizes ranging from 8x8 to 512x512. The convolutional processes are managed by an activation layer, which selects essential features. A leaky rectilinear unit (LReLU) is employed for VGGNet-19, allowing for variance-based feature extraction for improved accuracy performance. The leaky RELU utilised in this scenario eliminates 5% of all low variance features and aids in the initial feature selection phase.

However, the Leaky ReLU has the drawback of estimating variance based on a fixed threshold, which is inefficient for large datasets. A layer called MaxPooling (maximum variance pooling) is utilised to improve feature selection capabilities. By computing a variance-based threshold for each extracted feature set, this layer selects features according to this variance threshold. If a feature's intensity exceeds this cutoff, it will be advanced to the following level; otherwise, it will be discarded at the current level alone.

Hyperparameter optimization is used to change the pooling probability in order to optimise feature selection. To estimate a large number of features from the provided satellite images, this procedure is repeated for various step sizes and windows. These operations are made available to an FCNN (Fully Connected Neural Network) model for image classification into damage severity kinds and crop types.

The classification layer employs a Soft Max Activation Model to estimate the final class probability, which aids in classifying the severity of the crop damage. The Soft Max Activation Model includes the ability to backpropagate, which helps with ongoing accuracy improvement.

For adaptive threshold evaluation with parameter adjusting procedures, these classes are employed.

Before activating an adaptive thresholding layer for final processing and ongoing accuracy improvement the CNN Model measures crop type and damage severity. Depending on the season in which the image was taken, the layer employs various thresholds for the R, G, and B components to evaluate various damage kinds.

When the test set image closely resembles one of the training set images, the correlation value is over 0.999. In certain situations, the test set image is discarded and not used for parameter adjustment. In such situation, we had to upload new images to the CNN architecture in order to retrain it. Because of this, the model is constantly updated, and its accuracy gradually increases. The examination of accuracy performance was covered in the text after along with numerous other performance indicators.

III. ANALYSIS OF RESULT AND COMPARISONS

We have divided the result on two sections visual analysis and quantitative analysis.

A. Visual Analysis

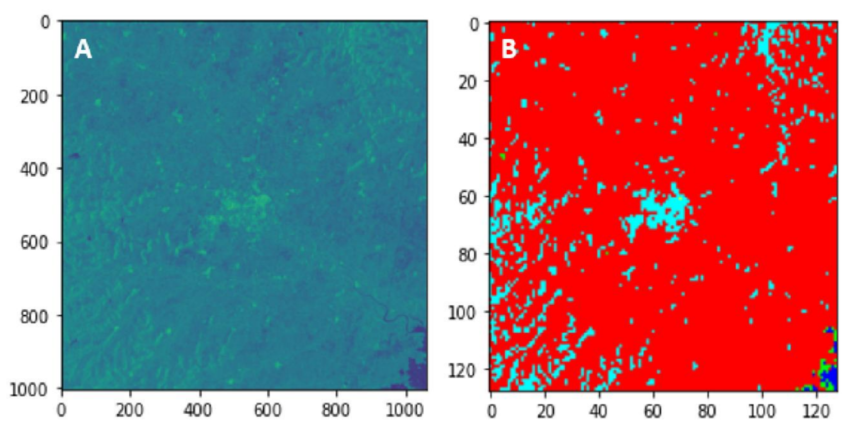

Figure 3: Experimental Results

As demonstrated by figure 3, (A) are the input images and figure 3, (B) shows results for the proposed model.

B Quantitative Analysis

The data was collected in and around the Amravati area (77.7523, 20.9320) from 2015 to 2021, and analysed using the suggested model. The recommended model employs Google Earth Engine for collecting of a wide variety of datasets from MODIS satellite data collections. Also, USGS SRTMGL1 ground elevations and the COPERNICUS subset were utilised for dataset collection. The Rice, Bajra, Cotton, and Wheat crop images were retrieved for this model data set in 3 distinct severity categories. The data set have 2000 images in total which are classified in the following ratios: 70:15:15 for training, testing, and validation.

Performance was evaluated for publications in [8], [6], and [16], by putting the precision score from the literature so that we can compared the proposed model concerning the accuracy values. The results concerning the evaluation of different testing images as shown in Tables By combining CNN with incremental learning, with several high-performance classification and adaptive thresholding level we were able to obtain decreased error rates. Based on this dataset collection, accuracy was examined by equation 4

$$A = \frac{N_C}{N_T} * 100 \ldots (4)$$

Where, $N_T \& N_C$ represents total number of images used for classification and number of correctly classified images. The model is compared with the state-of-the-art methods like HCNN, CNN TSS, MSRPS. The table 1 show the comparison of this methods with respect to number of images used for evaluation (NI).

Table 1. Accuracy Scores of Various Algorithms

Number of input images	Accuracy Values for MSRPS [6]	Accuracy Values for HCNN [8]	Accuracy Values for CNN TSS [16]	Accuracy Values for Proposed Model
100	65.55	73.22	83.93	96.66
500	66.57	74.36	85.24	97.8
1000	66.78	74.60	85.51	98.03
1500	66.79	74.61	85.53	98.04
2000	66.80	74.62	85.54	98.05

The output of suggested model 15% better than HCNN & MSRPS and at least 12.5% improvement when compare to the Convolutional Neural Network TSS, in terms of multiple domain accuracy performance.

Effective feature extraction using incremental learning leads to better feature selection. It enhances classification efficiency across a range of satellite image classification applications and improve the speed of classification. As a result, it is appropriate for real-time applications.

IV. CONCLUSION

To increase overall precision, accuracy, recall, and AUC, the proposed architecture combines DL (Deep Learning) with augmented dataset acquisition and incremental learning. Because of these features, the proposed model achieved accuracy of 98.05%, for various image types. In terms of multiple domain accuracy performance, the developed model outperformed CNN TSS by 12.5% and MSRPS by at least 15%. Across diverse image types, the implemented model had a low latency of 6.85 ms. As a result, this type is excellent for a variety of high-speed applications.

To find out the gap in the suggested model researchers can also verify the suggested version's overall performance on various datasets. The researchers can use Q-Learning and ensemble classification models to enhance accuracy and precision.

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