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Categorizing Sentinel-2 Images Based On Binary-Weighted VGG-16 Network

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Abstract: Intelligent In a wide range of applications, including the classification of land cover and environmental surveillance, satellite imagery is essential. High-resolution multispectral images from the Sentinel-2 satellite project offer helpful information for a variety of Earth observation needs. In this paper, a brand-new binary weighted VGG-16 (BW-VGG) method for classifying Sentinel-2 images is proposed. In this study, we propose a binary weighting strategy that increases the discriminative strength of the network by giving more weight to more relevant spectrum bands. The model's training set was the multidimensional Sentinel 2 photo with its 13 spectrum bands. The featured photographs were categorized into several classes to build the dataset for the study area. By using the fruit fly optimization (FFO) method, the proposed model's accuracy is increased even more. The suggested approach was found to have the highest accuracy. Results from experiments show that the proposed approach is more effective than existing approaches at classifying Sentinel-2 photos.

Keywords- *Satellite imagery, Sentinel-2 images, binary weighted VGG-16 (BW-VGG), fruit fly optimization (FFO)*

1. Introduction

Sentinel 2, a European Space Agency (ESA) spacecraft project, changed the study of Earth with its high-resolution multidimensional photos covering the planet's crust. These pictures contain an enormous amount of data that can be used for a variety of purposes, ranging from ecological observation to urban planning and farming analyses [1]. However, efficiently analyzing and understanding such massive volumes of information necessitates complex approaches, one of which is Sentinel 2 visual categorization. The method of categorizing pixels or areas under Sentinel 2 images into distinct groups or categories of land cover is referred to as categorization [2]. The process is critical in obtaining useful data and getting ideas on numerous features of the planet's outermost layer, such as plants, reservoirs, and regions. Scientists and practitioners can properly organize and comprehend every characteristic available in these pictures by utilizing methods for categorization and procedures [3]. The abundant spectrum data recorded by the spacecraft serves as one of the major hurdles in identifying Sentinel 2 photos. The multidimensional detector on Sentinel 2 collects information in many band structures covering transparent to infrared rays. Such a broad spectral range enables the differentiation of diverse landscape groups according to their distinct illumination qualities. The level of difficulty stems from the requirement of evaluating and analyzing each band at the same time, taking into account their connections and linkages [4].

To solve this issue, scientists and professionals created a variety of categorization methods for Sentinel 2 photos. Such approaches include both conventional methods, such as probabilistic categorization and assist vector models, in addition to more contemporary advances for deep algorithmic learning, known as neural networks with convolution [5]. These methods use machine learning and artificially intelligent systems to acquire knowledge and recognize trends in pictures, allowing for precise and effective categorization. The results of identifying Sentinel 2 photos are extremely useful for a wide variety of purposes. In ecological monitoring, for example, categorization outcomes can aid in the detection and tracking of modifications to the distribution and extent of land over the years, assisting in evaluating the effects of forest destruction, urban expansion, and environmental damage [6]. Determining Sentinel 2 pictures for agricultural use helps in tracking plant varieties, checking the plant's wellness, and optimizing watering and fertilization practices. This sorting can also help in disaster recovery and urban planning by recognizing susceptible locations, measuring destruction, and assisting in efforts to rebuild [7].

The following portion of this paper is structured this way: Part 2-Related Works, Part 3-Methods, Part 4- Results and discussion, and Part 5- Conclusion.

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2. Related Works

The efficiency of extracting features for cloud categorization was improved using an updated DL architecture named CloudNet. Residual knowledge was integrated into CloudNet to transmit geographical data and stop the reduction of geographical data brought on by adding more levels. To maintain the size of the source characteristic chart and the measurement of the resulting feature map at each level, the downsampling method was eliminated from CloudNet [8]**.** This research analyses the unique potential provided by Sentinel-2(S2) data for the massive classification of forests and forest species. A set of wavelengths were generated for each of the two cloud-free S2 scenarios. Following choosing parameters, we used a random forest classifier to perform guided pixel-based categorization. A preliminary model of categorization was developed with the goal of constructing a forest map of the Belgian Ardenne ecoregion [9]. They provided a frequency and geographic focus component in the advanced UNet to generate an approach for classifying icebergs using publicly accessible Sentinel-2 satellite data. Using Sentinel-2 imagery, the suggested technique was able to locate ice across the Nyainqentanglha range, addressing the frequency-comparable characteristics and the geographic association between ice along with particles [10]. The study [11] was to use ANN classification with Sentinel-2 imagery to classify mangroves. They carried out two key research involving data characteristics and hyper-parameter adjustment. Following these tests, they proposed a feasible ANN model for restricting mangrove spread using Sentinel-2 satellite data, topography, and height of the canopy data.

In the study [12], they describe an automated way of categorizing for predicting landscapes utilizing Sentinel-2 satellite picture information collected across a multi-temporal range. The graphical variety of the various areas of land throughout weather makes it difficult to separate multi-temporal photos spanning from any period of an ordinary calendar. This solution solves the issue. This technique further recognizes and categorizes a variety of various land cover classifications, not just distinct tree species or distinct crop types, for instance. In order to precisely determine the spread of P. oceanica and C. nodosa in the transparent and uniform, visually low-depth waters of the Thermaikos Gulf, Aegean Sea, Italy, they used weather and aquatic column adjustment together with three distinct classification methods (Maximum Likelihood Classifier (MLC), RF, and Support Vector Machines (SVM)). They have developed a location-specific method using the blue and green Sentinel-2A bands to determine the water depth of the SE Thermaikos Gulf. The techniques described in their work collectively offer a ready-to-use strategy for surveying aquatic grasses and subsurface ocean communities in a variety of coastal environments [13]. The study [14] goal was intended to evaluate the effectiveness of a technique that has been effectively used to classify hyperspectral Sentinel-2 data using both controlled and uncontrolled methods. This approach has the benefit of integrating the quantity description rather than just the fundamental frequency signature appearance of the pixels. The quantity appearance gives details at the sub-pixel range and can theoretically depict the landscape more precisely. The differences among the recognized cadastral information and clear usage of the human vector modeling and pixel-based categorization images from satellites Sentinel-2 were visible in the extent of the forest-covered and woodland regions. It offers justifications for automating the procedure of locating unmanaged development of forest zones. The extent of the plantation and shrub attack management in the area where farming has ended is not accurately reflected by cadastral records, which are out-of-date [15].

3. Methods

3.1 Dataset

Sentinel 2, a multidimensional satellite photograph having 13 different frequency bands, was used in order to tackle the problem of categorizing land utilization with Land Covering [16]. Specifications of 10 m, 20 m, and 60 m, as well as a five-day repeat period, were used to map the whole geography of the World. In the research we conducted, four of the 15 frequencies with a length of 15m had been utilized in B4, B5, B6, and B9. The extensive satellite information will have an impact on the division of Land Cover when machine learning or deep learning techniques are used. Thereby, utilizing the Sentinel 2 information and advanced algorithms for deep learning were combined to provide an enormous quantity of knowledge that would boost the effectiveness of the algorithm applied. To create the marked database for picture categorization, both of the subsequent procedures were carried out.

- Picture Acquisition: Obtaining a cloud-free, orthorectified, and level 1C sentinel 2 photo for the research region.
- Database Generation: Using the information collected, a collection of 19000 annotated and geo-referenced photo updates, every one of 64 × 64 pixels in size, was constructed and individually validated.

3.2 Satellite Image Acquisition

Sentinel 2 satellite footage was gathered for the research location, the Davanagere zone of Karnataka, in April 2021 [16]. Copernicus provided the raw spacecraft photos that had been orthorectified and atmospherically adjusted. The captured picture had been processed to produce a False

Colour Composite (FCC) image, which had been then mosaicked to include the whole area of interest (AOI), and this was primarily collected below four tiles, subsequently attached to produce an analysis region through GIS software, and then modified to tiny regions of 64 × 64 resolution and separated into distinct categories.

3.3 Collection of dataset

The collection contains 20000 annotated photos from 5 classifications. Each class has 2800 photos for learning, 600 for confirmation, and 600 for evaluation. The data gathered from satellite pictures and the results of the region of analysis are stored.

Furthermore, data enhancement has been utilized to expand the number of databases by including lightly altered duplicates of previous photos, allowing it improves the range of examples in the collection as well as provide the greatest precision and apply the predicted results for greater evaluation data. The sample images are patches from six classes, each with 64 × 64 pixels.

3.4 Binary weighted VGG-16 (BW-VGG)

'VGG' refers to the visual geometry group in Oxford, and the integer '16' indicates that its structure represents a 16-layered-deep neural network (VGGnet). Assume that we will begin with pixel-by-pixel assessing the RGB color-mapped information (picture). We will begin with a little section of the picture, indicate a pixel, and display it as a cubic shape wedge with certain dimensions, with the RGB (red, green, and blue) number of the pixel making up the vertical portion of the cuboid. The picture is now being looked at with a neural network. Following the subsequent procedure, we would obtain a fresh picture with reduced height and length but considerably more bands in place of RGB. Convolution is a phrase that fits with this process. The VGG16 model employed an approach of a comparable kind is shown in Figure 1. We must talk about certain methods of mathematics that went into developing this approach now. The results of each layer that follows could be computed numerically.

For convolutional layers, use the Equation 1:

$$Output = [(j - l + 2n)/t] + 1 \quad (1)$$

Where j is the resolution of the picture, l is the kernel size, n is the padding value, and t is the stride value.

Max pool layers are shown in Equation 2:

$$Output = [(j - l)/t] + 1 \quad (2)$$

Where j is the (input) image's dimension, l stands for kernel size, and t is the stride value.

The picture is first processed through the first level, which has two convolution layers (3 × 3 kernels, padding = 1px, stride = 2). This changes the picture's dimensions to 64 × 64 × 16.

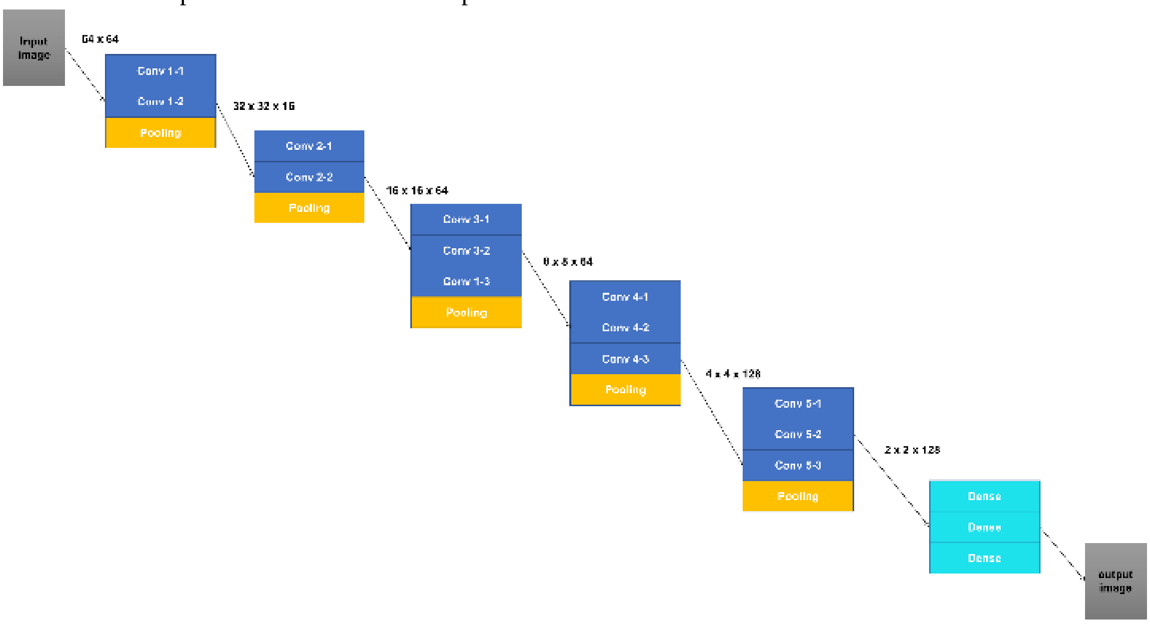


Fig 1: BW-VGG Architecture

Data will be forwarded to a max pooling layer having a pool count of 2 × 2 and stride = 2. The picture is then resized to 32 × 32 × 16 pixels.

The procedure reappears with the assistance of a separate set of two convolution layers, but this period includes 128 channels. So, despite the fact that the kernel size, stride, and padding stay constant. The picture's measurements could be converted to 32 × 32 × 64 using this approach.

This picture will be processed through a max pooling layer with kernel size (2 × 2) and stride value = 2, where the image parameters are transformed to 16 × 16 × 64.

This method is repeated till the final set of convolution and pooling layers produce their results. (picture size: 2 × 2 × 128) Last but not least, the picture (with size: 2 × 2 × 128) is processed through a set of three layers that are fully linked (often referred to as thick layers). These layers are applied to assemble the information taken from the earlier data set and deliver the end result classes.

3.5 Fruit-fly optimization algorithms (FFO)

The fruit fly has stronger smell and sight senses compared to other kinds, allowing them to fully utilize its natural ability to find food. Particularly, the fruit fly nose recognizes various flavor smells dispersed throughout the sky when it is located 50 km beyond its meal source. When fruit insects get close to the food supply, they use their responsive sight organs to detect the food and the organization's gathering place and then immediately fly in that way. Throughout the procedure, the information about the best fruit fly is going to be disseminated to the complete group together, and the following attempt is going to depend solely on the information of the previous best fruit flies.

FFO can be divided into distinct phases according to the following food-seeking characteristics of a cohort of fruit flies:

Stage 1. Parameters initialization

Set the FFO variables, including the greatest amount of iterations, the sample dimensions, the beginning point of the fruit fly group (W_axis, Z_axis), and a randomly chosen flight distance limit.

$$W\_axis = rands(1,2) \tag{3}$$

$$Z\_axis = rands(1,2) \tag{4}$$

Stage 2. Initializing the population

Provide an arbitrary position (W_j, Z_j) and distance for a particular fruit fly seeking sustenance, where j denotes the population amount.

$$W_j = W\_axis + RandomValue \tag{5}$$

$$Z_j = Z\_axis + RandomValue \tag{6}$$

Stage 3. Population estimate

Initially, determine the distance between the current position of the product and its source C. After that, calculate the scent strength judgment value (T); this is the inverse of the food's position relative to the source.

$$C_j = \sqrt{{W_j}^2 + {Z_j}^2} \tag{7}$$

$$T_j = 1/C_j \tag{8}$$

Stage 4. Replacement

Change the scent percentage judgment value (T) with the scent percentage judgment process in order to determine the scent percentage ($Smell_j$) of each fruit fly position.

$$Smell_j = Fuction(T_j) \tag{9}$$

Stage 5. Identify the highest scent percentage

Identify the fruit flies with the highest percentage of an odor and their position within the fruit fly colony.

$$[bestSmellbestIndex] = max(Smell) \tag{10}$$

Stage 6. Maintain the highest scent determination

Keep the maximum scent percentage number and W and Z dimensions. The fruit fly colony then flies in the direction of the position with the highest percent of the odor.

$$Smellbest = bestSmell \tag{11}$$

$$W\_axis = W(bestIndex) \tag{12}$$

$$Z\_axis = Z(bestIndex) \tag{13}$$

Stage 7. Consistent optimization

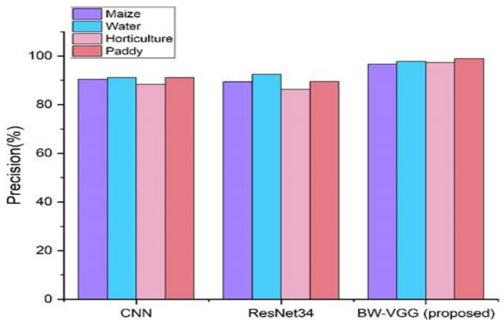
Provide the consecutive optimization process to replicate stages 2 through 5. When the scent percentage is no longer greater than the prior consecutive scent percentage or when the consecutive number achieves the maximum consecutive number, the flow ends.

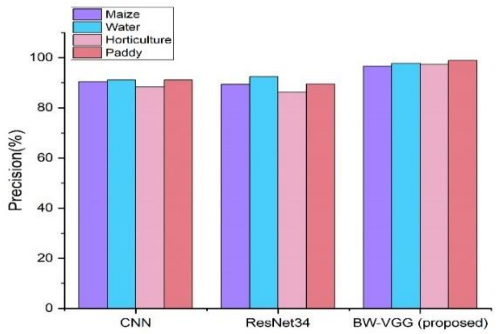
4. Result

On The existing approaches like Custom Neural Network Architecture (CNN), Residual Neural Network (ResNet34), and Binary Weighted Visual Geometry Group-16 (BW-VGG) had the parameters like "accuracy, recall, precision, and f1- score".

Precision is the degree to which a prediction is accurate. It is the number of related classes that were obtained. It determines how confidently several positive answers can be trusted. The existing approaches CNN and ResNet34, have an overall percentage of 91.2% and 92.7%, and our proposed method BW-VGG has an overall percentage of 98.9%, as shown in Figure 2. It indicates that our proposed technique has more precision.

$$Precision = \frac{Number\ of\ positive\ predictions}{Total\ number\ of\ positive\ predicts} \quad (14)$$

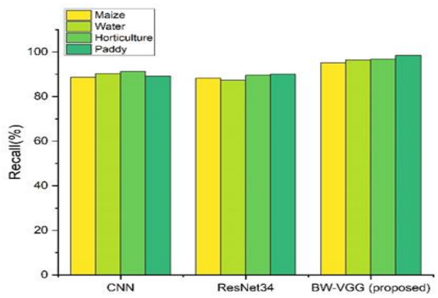




Fige 2: Precision

The percentage of correctly identified groups in an information set is called the recall. Figure 3 shows the overall performance of recall for CNN and ResNet34 in 91.2%, 90.1% compared with the proposed approach BW-VGG is 98.5%.

$$Recall = \frac{Number\ of\ the\ correct\ actual\ positive}{total\ number\ of\ actual\ positivies} \quad (15)$$



Fige 3: Recall

Accuracy can be defined as a measurement of the proportion of accurate projections produced by a predictive algorithm. The overall percentage of accurate comparison for existing CNN and ResNet34 is 91.3% and 93.6%, and our proposed approach, BW-VGG has an overall percentage of 99.5%, as shown in Figure 4. It shows that our proposed method is more accurate than the existing methods.

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ number\ of\ predictions} \quad (16)$$

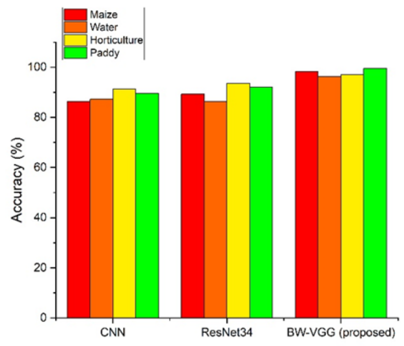


Fig 4: Accuracy

The F1 measure is calculated as the balanced average of both the recall and the precision classifications. It is also called as an estimation of the accuracy of an equation on an information set. It is employed to assess the binary system of categorization, which categorize instances as 'positive' or 'negative.' Figure 5 shows the existing approaches CNN and ResNet34 have overall percentages of 92.1% and 91.8%, and the proposed technique BW-VGG has a value of 99.6%.

$$F1\ Score = \frac{2 \times precision \times recall}{precision + recall} \quad (17)$$

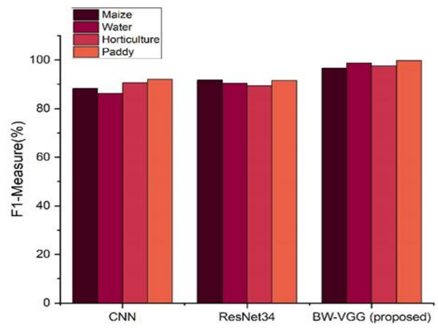


Fig 5: F1-Measure

5. Conclusion

In this study, a brand-new binary weighted VGG-16 (BW-VGG) approach for identifying Sentinel-2 pictures was proposed. We introduced a binary weighted method that improved the network's exclusive capability by assigning greater importance to better-suited spectrum bands. The multipurpose Sentinel 2 image with its 13 spectrum bands served as the model's training dataset. The designed model's accuracy is further improved by employing the fruit fly optimization (FFO) technique. The method presented has been shown to provide the best accuracy. The average accuracy of our proposed system was determined to be 99.5% when compared to the existing methods. Because of the model's limited flexibility and weight values, it could be challenging for it to take on other types of information or activities outside the unique challenge it was developed on. In the future, it could be able to get around some of the constraints related to binary weights and obtain better results by customizing the design and learning techniques to the particular demands of given challenges.

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