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Prediction of regional vegetation cover using spatial image features and semantic segmentation

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***Abstract*---**Vegetation is an essential part of our ecosystem; it also determines health of our planet. According to "The State of the World's Forests 2020" only 31% of the global land area is covered with vegetation. This paper presents a superior way of representing vegetation cover in a region by utilizing Atmospherically Resistant Vegetation Index (ARVI) as vital features out of multispectral satellite images. These images comprise Green, Blue, Red and Near Infrared bands data which was further utilized by U-Net to efficiently segment satellite images. In remote sensing greenery of environment is traditionally determined using NDVI, one of the critical imperfections with this method is that it is liable to compute inaccurate values as a consequence of variations in soil, air moisture and shadowing affected by varying incidence angle of sunlight. On the other hand, ARVI is immune to such flaws and integration with deep learning provides a better solution for segmenting regional vegetation and predicting its coverage up to some extent. This method can be employed for predicting vegetation in any region along with assisting in events such as repopulating trees and urban planning while conserving beauty of our nature.

***Keywords*---**multispectral, atmospherically resistant vegetation index (ARVI), normalized difference vegetation index (NDVI), near infrared (NIR), maharashtra remote sensing application centre (MRSAC), U-Net, remote sensing.

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Introduction

Vegetation is a standard term used for describing the life of plants in a distinct region. In our solar system earth is a planet which is in Goldilocks zone which allows the proper amount of heat, air and water for flourishing life. It is our responsibility to look after our planet and environment. Earth consists of four invaluable wonders namely hydrosphere, biosphere, lithosphere and atmosphere which are further distinguish into various sub-spheres. Biosphere includes the categorization of all the living organisms such as micro-organisms, plants, animals etc. and these all are interdependent for survival. In this paper the center of attention is vegetation health and analyzing the difference engendered overtime to make people aware of its change with the help of GIS and Remote Sensing. It is observed that the global forest health is declining over the years, to date, climate change and global warming have been a topic of interest for most empirical and synthesis researchers whereas the health of vegetation have been partially abandoned. There is a need to quantitatively measure and monitor the variation in vegetation health, there can be many different ways for defining vegetation health depending on frame of reference one can have. State of Art technologies in remote sensing dispense wide variety of methods for measuring the same with reasonable accuracy. India is among the first countries within the world to have stated scientific management of its forests. Even today the forest departments are managing the forests of the country under the corresponding state governments. Maharashtra Forest portal is one of an interactive portal governed by the Ministry of Forests Department of Maharashtra which provides interactive interface for forest GIS but not to an extent and is short on providing feature like information about vegetation cover and health for regions.

The primary aim of this paper is to analyze the regional vegetation by extracting spatial image features from multi-spectral Planet Imagery Product of Maharashtra Remote Sensing Applications Centre Nagpur obtained from Indian Remote Sensing Satellite and representing the segmented region based on different classes like Water, Live vegetation and Dry vegetation. Extracting multiple bands as features (mainly NIR, R, G and B). Computing ARVI from the extracted band data and training segmentation model for representing almost accurate segmented regions based on different classes. The proposed approach can be implemented on any multi-spectral satellite image of urban area consisting of land, vegetation, water bodies and other entities which are used in remote sensing and other industries working in the field of remote sensing. This method provides solution for understanding the regional vegetation government agencies like MRSAC, Forest Dept. of Maharashtra and others working on remote sensing data. In remote sensing, multispectral images are very efficient for analyzing and obtaining a better understanding of the earth (Bhandari, Kumar, & Singh, 2012). The remote sensing data has many application areas including forest type classification, soil moisture measurement, land cover classification, measurement of moisture/water in vegetation, oceanography, classification of type of sea ice, snow mapping (Ayhan. B, et al., 2012). The multispectral remote sensing images contains essential combination of spectral and spatial features of the objects. Remote sensing is a technology/process aimed at obtaining information about an object by analyzing data acquired from the object at a distance. It is mainly composed of four parts, first: Objects as entities or phenomena in an area, second: Data acquisition through certain instruments, third: Data analysis by some devices and fourth is representation of analyzed data (Raju. A, Singh. A, Kumar. S & Pati. P, 2016). There are two fundamental methods of storing this acquired information in digital form- raster and vector. The term vector data can be defined as the data in which the features are sequentially recorded, and the shape of those features is defined by the numerical value of the pair of x and y coordinates. In raster data the whole region of an image is sub-divided into a grid of diminutive cells. Raster data can be deliberated as a matrix consisting different values. By enhancing the vegetation signature in combination with soil background effects, vegetation indices are designed to maximize vegetation signature (Jackson and Huete, 1991). Green healthy vegetation absorbs a great deal of red light with chlorophyll in the leaves, which is why red wavelengths are particularly evident, and vegetation reflects a great deal of NIR light with internal leaf structure. A barren land or soil reflects only moderately in both red and NIR wavelengths while unhealthy or sparse vegetation is more reflective in red wavelengths than healthy vegetation (Holme et al., 1987). Every index has its own downsides and advantages. NDVI is a numeric method that utilizes Red and NIR bands data to evaluate if the land cover comprises live and green vegetation or not (Roy. B,2021). This index NDVI was first proposed in 1973 by Rouse et al. Since vegetation absorbs the red and NIR bands of light, NDVI is derived by dividing pixel values by pixel absorbance Below equation 1.1 can be used to derive NDVI:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1.1}$$

The values range from −1 to +1, where −1 represents water and barren land, +1 corresponds to forests. It is mostly worthy for monitoring low to moderate density vegetation.

Atmospherically resistant vegetation index (ARVI) is a prospective developed to be utilized for remote sensing of vegetation from the Earth Observing System MODIS sensor. ARVI takes advantage of therness of the blue channel. It is actually possible to increase the resistance of the ARVI to atmospheric effects compared to the NDVI through a self-correcting process in the red channel. An atmospheric effect in the red channel is reversed by measuring the difference between the blue and red channels radiance (Somvanshi. S.S & Kumari. M, 2020). ARVI is convenient for observing vegetation cover in urban environments. It does not drench like NDVI and SAVI. Below Eq. (1.2) can be used to derive ARVI:

$$\mathrm{ARVI} = \left[\frac{\mathrm{NRI} - \mathrm{RED} - \mathrm{y}(\mathrm{RED} - \mathrm{BLUE})}{\mathrm{NRI} + \mathrm{RED} - \mathrm{y}(\mathrm{RED} - \mathrm{BLUE})}\right] \tag{1.2}$$

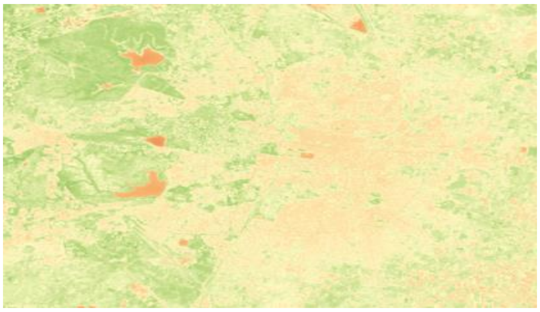

Fig. 1. Calculated NDVI for region of interest.

Fig. 2. Calculated ARVI for region of interest.

From Figure (1) & (2) we can clearly observe that ARVI highlights vegetation with greater extent in an urban area.

Materials and Methods

This paper proposed a better method for segmenting multi-spectral satellite imagery and leveraging the optimal use of R, G, B, and NIR bands. The specific Remote sensing satellite deployed for earth observation is capable of providing scene-specific spot imagery and can provide imagery with a spatial resolution better than one meter and a swath of 9.6 km. In this paper the area of 374km2 of Nagpur city 21.1458° N, 79.0882° E was analyzed. The data-set taken in consideration for this task contained images of different sizes, width and height along with corresponding masks before processing such non-uniform data can lead to severe miscalculation and can produce unexpected results so it is better to filter data using pre-processing techniques. The initial task is to combine different bands into a single image this method is knows as band stacking in which individual bands (red, green, blue, NIR) were stacked into single image with tif format preserving the raw information. After stacking resultant image appears to be dull hence enhancements are used to make visual interpretations easier and to understand imagery effortlessly. The benefit of digital imagery is that it allows to control the digital pixel values in an image. Post stacking of bands ARVI is calculated and the resultant image is stored.

Preparing Data

Multispectral image of Nagpur city were obtained from MRSAC and pre-processing tasks were performed as mentioned above along with the masks for different classes. This composite image after band stacking was initially 2235*1926 px further it was clipped into multiple patches of 255*255*3 px which include R, B and ARVI channels along with equivalent masks with 3 classes water, live vegetation and dry vegetation.

Filtering Data

It was observed that some patches did not contribute in storing the ROI, therefore the patches and masking having null values and unique pixel values of masks less than 5% of the image were eliminated and filtered from actual processed data. Data augmentation such as rotation, flip, etc. were performed to generate a synthetic dataset This helped in creating a large enough dataset to train U-Net for semantic segmentation.

Splitting data

The filtered data is further divided into training and testing sets into the proportion of 75% for training and 25% for testing in order to validate and evaluate the performance of our model. The ratio varies based on the size of the data. In case, the data size is gigantic, one can also prefer to go for a 90:10 data split ratio where the validation data set represents 10% of the data which will be tested.

Training U-Net

U-Net architecture which can be viewed in Figure (3) was mainly designed for bio-medical image segmentation which includes three main operation contracting path, expansion path and third is the final output. The entire deep learning is that the neural network tries to update the weights. This is an edge-to-edge fully convolutional network (Flood. N, Watson. F & Collett. L, 2019). It can be given any image size as input since it doesn't have fully connected dense layers.

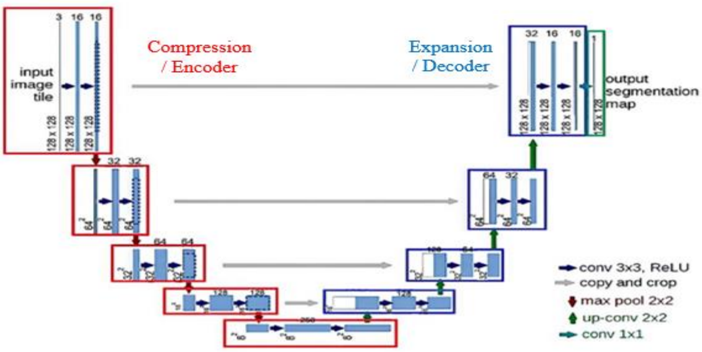

Fig. 3. U-Net Architecture.

Proposed Approach

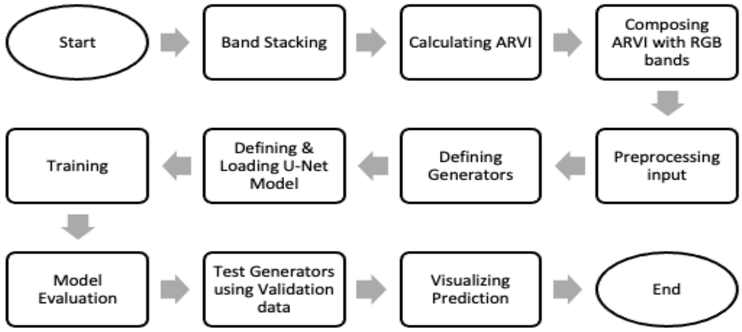

Fig. 4. Workflow

In this research regions in an image were analyzed and segmented based on the vegetation class they belong to. Initially multiple bands are combined together and a composite image is created using band stacking as described in section 2. Each pixel value been computed using ARVI technique utilizing information from Red and NIR bands which also includes setting the constant 'y' to 0.1 for eliminating the atmospheric errors and those which could not be resisted by NDVI. Next task involves extracting this ARVI computed features and creating a feature vector which can be further feed in to the deep learning model (U-Net) along with other channels. Further a function train generators() was defined to which image, mask and number of classes is passed as parameters for converting it into categorical data.

Further the number of training images including ARVI data and masks were defined, same was defined for validation purpose. As the task is to segment images based on multiple classes U-Net model utilizing backbone as 'resnet' was defined which used 'softmax' as activation function. Optimization is a mathematical regulation that determines the "optimal" solution in a quantitatively definite sense. Similarly, Adam optimizer is the extended version of stochastic gradient descent defined in 'keras'. This algorithm calculates the exponential moving average of gradients and square gradients. Using averages makes the algorithm converge towards the minima in a faster pace. The loss is determined using 'losses.categorical_focal_jaccard_loss' and matrix as 'metrics.iou_score'. Initially this model was trained for 15 epochs but training degradation was observed and further it was retrained for 25 epochs which resulted in better learning curve.

Results & Discussions

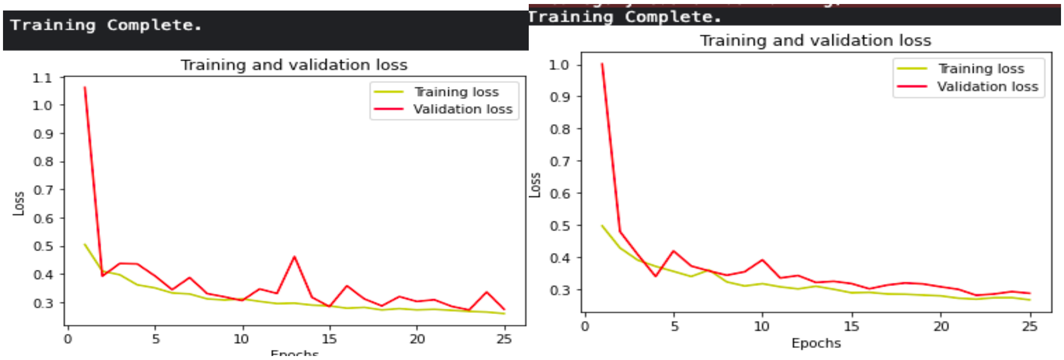

Fig. 5. RGB channel image loss *(Left),* RB+NIR channel image loss *(Right).*

The defined model was also trained on images consisting RGB channels only in order to compare the results with proposed work. Figure (5) gives insights about the results observed while training and validating the model. The training and validation loss were reduced up to 40% while considering the ARVI computed values and along with that it also benefited while predicting the vegetation Figure (5) RHS.

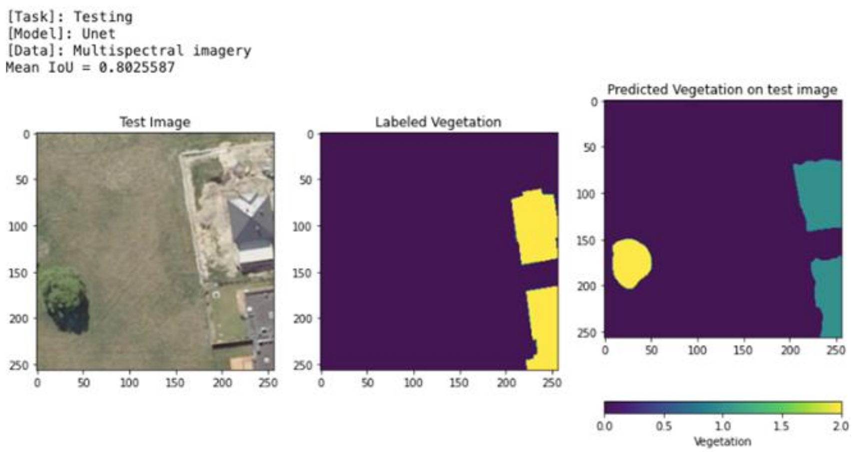

Fig. 6. Results of prediction in urban area.

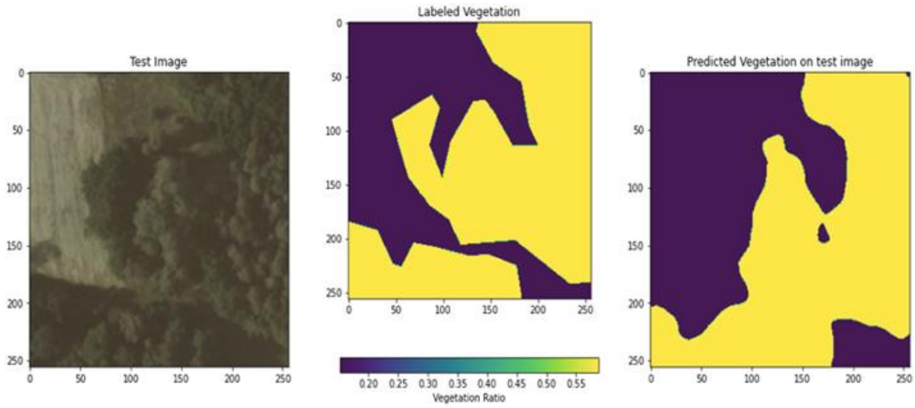

Fig. 7. Results of vegetation prediction in dense vegetation.

As discussed in section (3), left hand side is the contraction path also known as Encoder where regular convolutions and max pooling layers are applied through which size of the image moderately reduces while the depth slightly increases.

Proposed approach was evaluated and implemented on multi-spectral imagery of Nagpur region and an estimation of vegetation health was determined along with semantic segmentation. From the above Figure (6) it is clearly observed that the predictions made by proposed approach for segmenting the live vegetation (in yellow) and dry vegetation (in purple) are near accurate. This method efficiently segments the regions and shadows were eliminated as well, which might result in false computation of vegetation. In Figure (7) we can visualize that the ARVI (termed as vegetation on color scale) for the area covered by tree is much higher than that of construction and dry vegetation area, this model was successfully able to segment it (in yellow) with higher accuracy equal to or greater than 80\%. It states that calculating ARVI for the region and using it as input image for semantic segmentation can definitely help in reducing false calculations as this method reduces the effect of atmospheric scattering up to some extent than using NDVI images for segmentation. This work can benefit in city planning and reforestation in order to restore the natural balance linking plant life on earth for our better survival.

Conclusion

This work presented implementation of semantic segmentation of image for visualizing the difference in vegetation using band features from multispectral imagery. It was found that computing ARVI and segmenting multispectral images not only segments the vegetation as well as eliminates trees shadows close to accurate. In future work, initial plan is to study more profits of this index and to prepare a GUI where users can get estimation of vegetation heath of urban area without requiring much scientific data.

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