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Remote Sensing Based Agriculture Monitoring Using Convolution Neural Network

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Abstract: Remote sensing, a technique involves the use of satellites to gather data from Earth's surface has application across various domains. Over the past few decades, satellite imagery has been useful in large-scale land classification and monitoring agricultural activities. Agriculture monitoring has become very important to ensure food production and security. To maximize production and efficiently manage food supplies, accurate monitoring of agricultural activities on a larger scale is crucial. The Normalized Difference Vegetation Index, or NDVI, is a broadly utilized remote sensing indicator for agricultural management. This study addresses limitations in traditional monitoring methods by integrating Sentinel-2 satellite data with Convolutional Neural Networks (CNNs). The methodology involves preprocessing of satellite imagery and conversion to NDVI images, followed by classification technique to categorize into non-vegetated, stressed, and healthy vegetation classes. This project attempts to address the fundamental problems in traditional agricultural monitoring methods in order to provide farmers and other agricultural stakeholders a convenient and efficient alternative.

Keywords - Satellite Data, Agriculture Vegetation Health Monitoring, Deep Learning, Convolutional Neural Networks (CNNs), NDVI (Normalized Difference Vegetation Index).

Introduction

Crop monitoring involves regular and meticulous inspections of crops throughout the entire growth cycle. During crop monitoring, farmers traverse their fields to identify and address potential issues. The goal is to streamline farming activities, enhance user experience, and optimize yield. This technology empowers farmers to effectively manage multiple fields, reduce resource expenses, and make informed decisions [1]. By harnessing the power of satellite imagery and advanced visualization techniques, farmers and those involved in agriculture can use this solution to make well-informed decisions that will help maximize their crop yields., minimize resource usage, and enhance sustainability. NASA and ESA, along with other space agencies, have launched many satellites to observe Earth's land areas. The Sentinel-2 satellite, managed by the European Radar Observatory, stands out for its comprehensive monitoring capabilities. It covers global landmasses, coastal regions, and shipping routes with high-resolution imagery, and it contributes to the Copernicus initiative, a collaboration between the European Commission and ESA, by providing valuable data for various applications. To achieve frequent revisits and high mission availability, Sentinel-2A and Sentinel-2B operate together. The Sentinel-2 satellites each carry a single multi-spectral instrument (MSI) with 13 spectral channels within the visible/near infrared (VNIR) and short wave infrared (SWIR) spectral range [2].

Vegetation indices play an important role in crop development analytics, offering significant advantages in remote sensing technology. A plethora of vegetation indices, numbering over a hundred, have been developed from multispectral imagery. These indices utilize various combinations of spectral bands to quantify different aspects of vegetation health and dynamics. Among them NDVI is appealing because of its ability to quickly delineate vegetation and vegetative stress, which has great appeal in commercial agriculture and land-use studies [3]. Introduced in 1974, vegetation indices, including NDVI, facilitate remote observations of vegetation, crucial for assessing crop health, biomass, and chlorophyll content. It quantifies the amount of green biomass present in an area by analyzing the reflectance of near-infrared and red-light wavelengths, we can determine the Normalized Difference Vegetation Index (NDVI), which is a scale ranging from -1 to 1. Higher NDVI values signify lush and healthy vegetation, while lower values suggest sparse or stressed vegetation. This index is valuable for monitoring changes in vegetation over time [3].

NDVI is a remote-sensing approach used to quantify vegetation health. Higher NDVI values typically indicate healthier and more abundant vegetation, aiding in assessing crop health. NDVI is calculated using the following formula: NDVI = (NIR - RED) / (NIR + RED) [14]. NIR stands for near-infrared band, and RED represents the red band. Values close to 1 indicate healthy, dense vegetation. Values around 0.2 to 0.5 represent sparse or stressed vegetation. Values close to 0 or below indicate non-vegetated surfaces [14]. We consider bands 4 and 8 for the calculation of NDVI, which are Red and NIR channels respectively [12].

In this paper, we formulate an approach where classification is done on basis of types of vegetation based on colour codes obtained with the use of NDVI. Color codes assigned for healthy, dense vegetation is represented with the help of dark green color, for sparse or stressed vegetation is represented using light green or light yellow color and for non-vegetated surfaces are indicated using orange or red color. Further, the final classification is done through Convolution Neural Networks (CNN). We aim to develop a method for monitoring agriculture using satellite communications data and deep learning techniques. The novelty of this research is the integration of Sentinel-2 satellite data and training and evaluation of deep learning models like Convolution Neural Networks (CNN), which helps farmers learn about their crop health, and based on the results further assist them to implement precision agriculture practices, optimize resource usage, and improve overall crop productivity.

I. Literature Survey

Jindo et al. [4] highlights that there is a rapid expansion of remote sensing technologies in agriculture, especially the Synthetic Aperture Radar (SAR) system, yielding an impressive accuracy rate of 98.46% [4]. Kubitza et al. [5] developed yield models by regressing the MTCI (MERIS Terrestrial Chlorophyll Index) by employing RF algorithm that gave accuracy of 93.5% on crop cutting or crop model simulation data [5]. Foster et al. [6] claim that there are three main methodological approaches that estimate the irrigation water use that reflect the primary type of satellite data with the help of Evapotranspiration (ET) estimation algorithms and Variable Infiltration Capacity (VIC) model giving estimated accuracy of 90% [6].

Nguyen et al. [7] created a framework which is a novel rice mapping approach that combines data that is spatial, spectral and temporal; and has two main components: streaming data processing for raw image collection and cleaning, by employed classifier algorithms like SVM, CNN and Bi- LSTM which gave the accuracy of 93% [7]. F. Maselli et al. [8] conducted some investigations which showcased the possibility of combining standard meteorological data and Sentinel-2 Multi- Spectral Instrument (MSI) NDVI images to derive the Evapotranspiration (ETa) coefficients on Mediterranean croplands. The major crops in discussion here are tomato and corn. These food crops gave Irrigation Water (IW) variance over 50% and 70% [8].

Considering the example of World bank project, that also involved classification mapping, Random Forest is one of the popular methods of machine learning used by the decision tree ensemble and is used for classification tasks. Kussul et al. [9] developed a decision tree which is based on training samples, using the concept of information entropy. The overall accuracy of this classifier was 94.8% [9]. D. Murugan et al. [10] claim that the repeated usage of drone has to be minimized and hence an adaptive classification approach is developed which works with image statistics of the selected regions. The producer accuracy obtained for sparse and dense vegetation classes as 90% and 83.87% [10]. C. Qu et al. [11] proposed a spectral index known as Winter Wheat Index (WWI) which uses multi-temporal NDVI data to highlight and map winter wheat. This index has overall user and producer accuracy for winter wheat all above 91%. The F-score was over 90% [11].

table 1: summary of literature review

Paper Name	Methodology	Accuracy
Jindo et al. [4]	Remote sensing technologies like Synthetic Aperture Radar (SAR) System provide clear information on efficiency of photosynthetic processes [4].	98.46%
Kubitza et al. [5]	Yield models developed by regressing MTCI (MERIS Terestrial Chlorophyll Index) by using Random Forest Algorithm [5].	93.5%
Foster et al. [6]	There are 3 main methodological approaches that use Evapotranspiration (ETa) estimation algorithms and Variable Infiltration Capacity (VIC) model [6].	90%
Nguyen et al. [7]	Novel rice mapping approach developed using algorithms like SVM, CNN and Bi-LSTM [7].	93%
F. Maselli et al. [8]	Investigations on NDVI images to derive Eta coefficients on croplands. Irrigation water (IW) variance values obtained for tomato and corn [8].	50% (tomato) 70% (corn)
Kussul et al. [9]	World bank project that involved classification mapping studied. Decision tree based on training samples developed using Random Forest Algorithm [9].	94.8%
D. Murugan et al. [10]	Adaptive classification approach developed which uses image statistics of selected regions of mostly sparse and dense vegetations [10].	90% (sparse) 83.87% (dense)
C. Qu et al. [11]	Winter Wheat Index (WWI) proposed to highlight and map winter wheat [11].	91%

Table 1 provides a comprehensive comparison of literature reviews focused on various aspects of agriculture monitoring. It outlines methodologies, and findings from each study, facilitating a comparative analysis of the existing research. The comparison includes factors such as the scope of the review, techniques employed. and the main conclusions.

II.PROPOSED SYSTEM

3.1 Problem Statement

Traditional agricultural monitoring methods are expensive and imprecise due to manual inspections and limited data coverage. The inability of offering timely and complete insights across broad agricultural landscapes restricts farmers' attempts to optimize resources and maximize yields, affecting food security. To address this difficulty, we propose a system that combines remote sensing and deep learning. The methodology uses Convolutional Neural Networks (CNNs) to quickly identify irregularities using satellite images, allowing for improved agricultural management techniques.

3.2 Data Description

The European Space Agency (ESA), in charge of the Sentinel-2 earth observation mission, offers 10 days of worldwide coverage with a single sensor and 5 days of coverage with two sensors, S2A and S2B. It offers information in 13 spectral bands with varying spatial resolutions for selectable bands (10, 20, and 60 m) [12]. For our proposed method, we are using images of annual crops, permanent crops, and pastures from the dataset [12], taking into account bands 4 and 8 for our suggested work, which have Red and NIR (Near Infra-Red) channels, respectively [12]. The distinct spectral traces of water, bare terrain, agricultural land, thick vegetation, and related characteristics can be uniquely identified using the different combinations of these bands [13].

3.3 Methodology

The proposed methodology of our work is shown in figure 1.

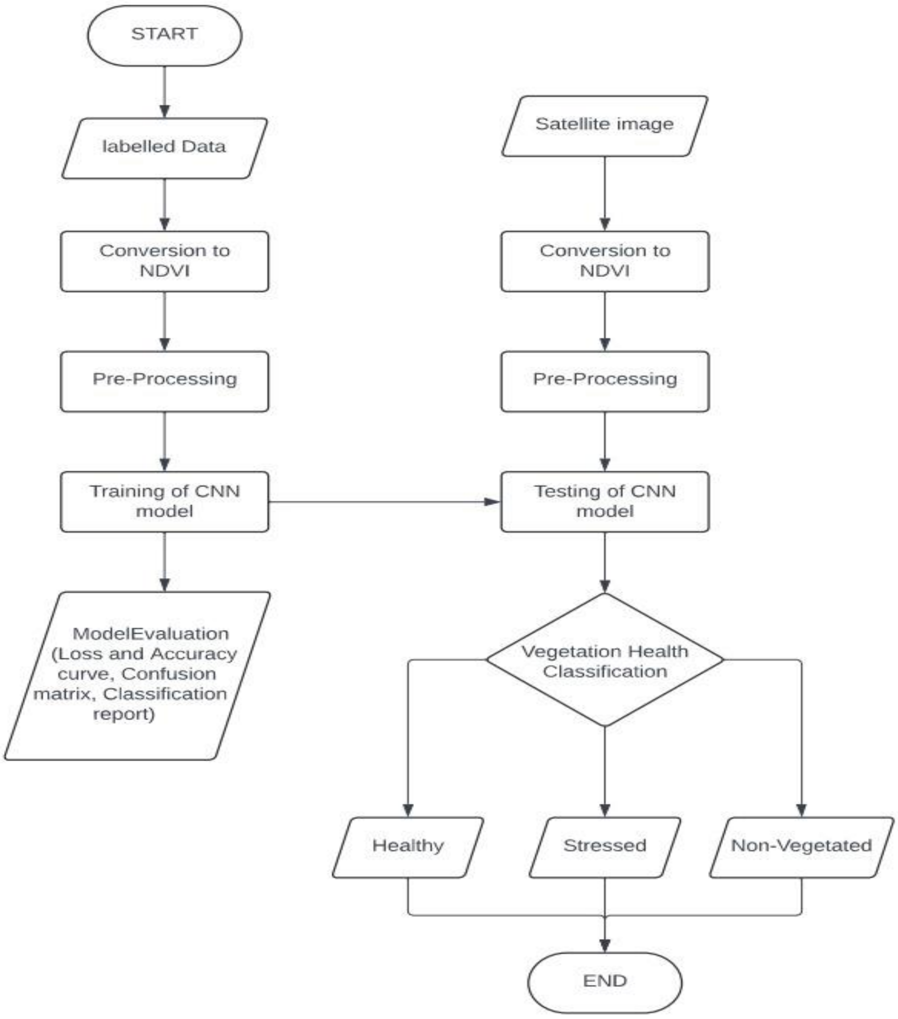


figure 1: flowchart

Step 1: Conversion to Normalized Difference Vegetation Index (NDVI), preprocessing and assigning classes based on color codes: The input image consists of data in 13 spectral bands and is of the .tif extension. The converted image is of the .png format. Preprocessing is then applied to the image where noise is removed, and image is resized. NDVI values can be visualized using color codes. Healthy, dense vegetation is represented with the help of dark green color. Sparse or stressed vegetation is represented using light green or light yellow color. Non-vegetated surfaces are indicated using orange or red color.

Step 2: Classification by Convolution Neural Networks (CNN): Based on the color codes, the images are classified into 3 different classes. A CNN model is built, trained and tested using the same. Figure 1 represents the flowchart of proposed system.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 128)	4736
max_pooling2d (MaxPooling2D)	(None, 63, 63, 128)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	73792
max_pooling2d_1 (MaxPooling 2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 64)	36928
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 128)	6422656
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 3)	387

figure 2(a): model summary

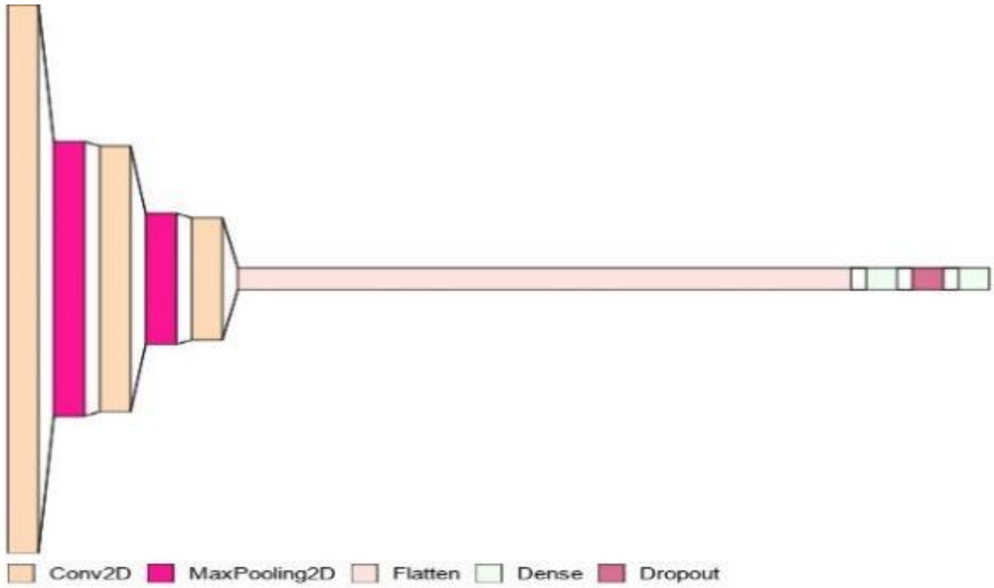
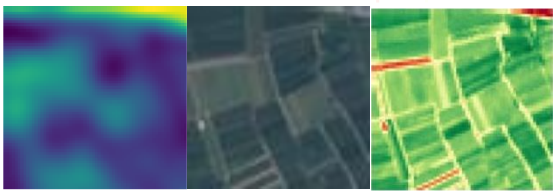


figure 2(b): model architecture

Figure 2(a) shows the model summary and 2(b) overviews the architecture the CNN model. The input image of size 128x128, is passed through a convolution layer having 128 layers and kernel size 3x3, followed by max pooling layer to downsize and capture the features from the image. This is repeated again one more time where the number of layers is reduced to 64 in the convolution layer and after undergoing max pooling, it is once more passed through the final convolution layer having 64 layers to learn more features. The kernel size for the convolution layer is 3x3, and strides for the max pooling layer is 2x2. The activation function used in the convolution layers is Rectified Linear Unit (ReLU) function. Next comes the flatten layer which converts the feature map into a format that dense layer can recognize. The dense layer here consists of 128 layers and uses the ReLU activation function. After that, a dropout rate of 0.5 is applied to the dense layer to prevent the network from overfitting. The final dense layer consists of 3 layers which are for the classification work using the Softmax activation function.

III. RESULT AND DISCUSSIONS

The images of Sentinel-2 in different formats namely TIF, RGB and NDVI equivalent are shown in Figure 3 (a), (b), and (c). The image size is 64x64.



(a) (b) (c)

figure 3: sentinel-2 image containing (a) all spectral bands and in .tif format, (b) RGB spectral bands and in .jpg format, and (c) equivalent NDVI converted image in .png format

As NDVI values can be visualized, we have assigned color codes based on the values range of NDVI. As seen in figure 4 (a), (b) and (c), the color code in which our model classifies are dark green for healthy, dense vegetation, light green to light yellow for sparse or stressed vegetation and orange/red for non-vegetated or bare areas.

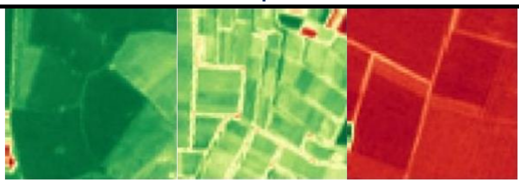


Figure 4: Color codes based classified vegetation images for, (a) healthy, dense vegetation, (b) sparse or stressed vegetation and (c) non-vegetated or bare areas

Now, the images are classified using Convolution Neural Network (CNN). Figure 4 shows the classified images obtained.
Table 2 represents the results of 3 distinct models' accuracy. We have trained and tested these three models with slight difference in their hyperparameters which includes the number of layers in Dense layer and rate of Dropout layer. The model has been trained using 3000 images and tested using 300 images. The architecture of all the below models is the same as depicted in Figure 2(b).

table 2: results of models' accuracy

No. of Layers in 2nd last Dense Layer / Rate of Dropout Layer	**Optimizer used**	**Training Accuracy for 10 epochs**	**Training Accuracy for 20 epochs**
128 / 0.5	Adam	87.53%	94.97%
64 / 0.2	Adam	85.57%	92.77%
128 / 0.5	RMSprop	93.43%	94.17%

The first model has 128 layers in the second last dense layer, which used the ReLU activation function and has a dropout rate of 0.5. On employing the Adam optimizer, this model achieves a training accuracy of 87.53% when trained for 10 epochs, which further improves to 94.97% when trained for 20 epochs. In comparison to the first model, layers in the second last dense layer and dropout rate, both have been reduced to 64 layers and 0.2 respectively. This model also utilizes the Adam optimizer, which gives a training accuracy of 85.57% after 10 epochs and 92.77% after 20 epochs. The third model is similar to the first one, however, it employs the RMSprop optimizer. The training accuracy achieved by this model after 10 epochs is 93.43% and after 20 epochs is 94.17%.
After closely examining the data, it is clear that the first model performs better than the others, especially after 20 epochs of training. Although the model's layer parameters are comparable to those of the third model, it appears that utilizing the Adam optimizer is what gave it its superior accuracy over the second and third models

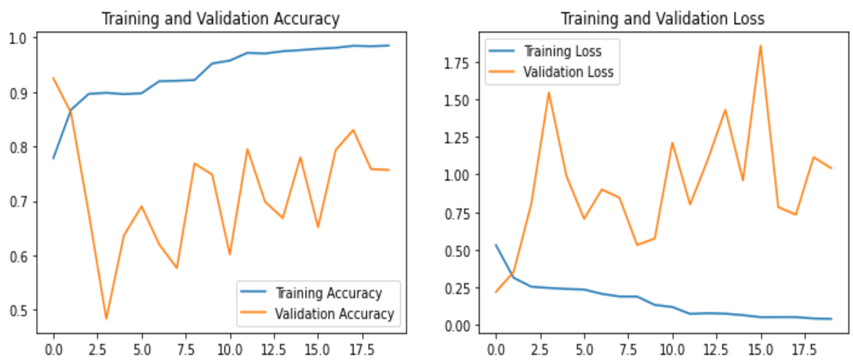


figure 5: training vs validation curve

Figure 5 depicts the training vs validation accuracy and loss curve. The model has been trained for 20 epochs.

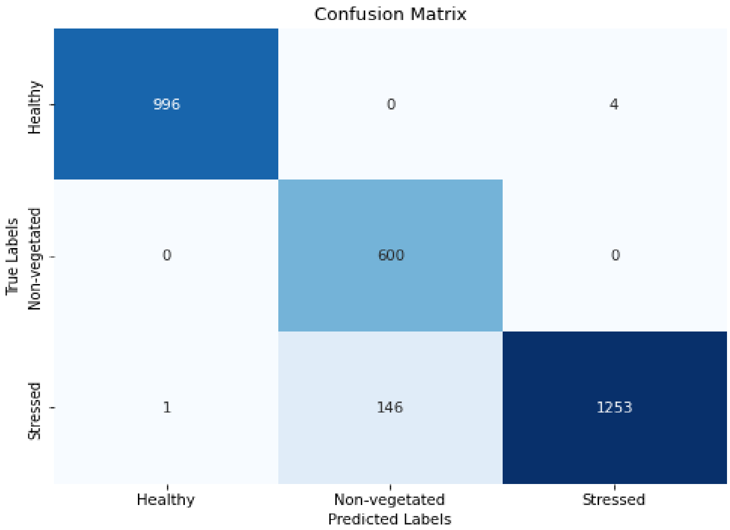


figure 6(a): confusion matrix

Classification Report:

	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	1000
Non-vegetated	0.80	1.00	0.89	600
Stressed	1.00	0.90	0.94	1400
accuracy			0.95	3000
macro avg	0.93	0.96	0.94	3000
weighted avg	0.96	0.95	0.95	3000

figure 6(b): classification report

Figure 6(a) depicts the confusion matrix for the model trained on the provided dataset. The model accurately predicted 996 instances of the "Healthy" class. Similarly, for the "Stressed" class, the model achieved a high accuracy, correctly identifying 1253 instances. For the "Non-vegetated" class, the model correctly predicts 600 instances. However, despite these, there were instances of misclassification. Four instances of "Healthy" were incorrectly classified as "Stressed". 146 instances of "Stressed" were misclassified as "Non-vegetated", suggesting a need for further refinement in recognizing stressed vegetation. Additionally, one instance of "Stressed" was erroneously predicted as "Healthy".

Figure 6(b) shows the classification report, providing a detailed summary of a classification model's performance across the three classes. The model achieved perfect precision (1.00) for "Healthy" and "Stressed" classes, however, for the "Non-vegetated" class, the precision is 0.80. The model demonstrated high recall (1.00) for "Healthy" and "Non-vegetated" classes, while for the "Stressed" class, the recall is slightly lower at 0.90. F1-score achieved are 1.00 for "Healthy", 0.89 for "Non-vegetated", and 0.94 for "Stressed".

The overall accuracy achieved by the model is 0.95, the macro average precision, recall, and F1-score attained are 0.93, 0.96, and 0.94, respectively, and the weighted average precision, recall, and F1-score are 0.96, 0.95, and 0.95, respectively.

IV. Conclusion

Accurate and timely data on crop growth is vital for enhancing farm management, ensuring food security, and facilitating secure grain trade. Using remote sensing to monitor crop health over large regions at a cost-effective manner can yield insightful data that helps farmers make well-informed decisions. In this paper, we have employed Convolution Neural Networks for classification of crop health on the basis of Normalized Difference Vegetation Index (NDVI), into three different classes - Healthy, Stressed, Non-Vegetated. We have achieved an accuracy of 94.97% and F1-Score of 0.94. Future works may include improving the method for other regions and crops using other deep learning algorithms and reinforcement learning.

V. ACKNOWLEDEMENT

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