https://doi.org/10.48047/AFJBS.6.14.2024.5120-5130

AFJBS

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

Crop Detection Using Remote Sensing Images

M. Devaki [1], S. Vishnukumar [2], V. Vasu [3], D.P. Sri Ragunath [4]

[1] *Department of Electronics and Communication Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India. devakimjj@gmail.com*

[2] *Department of Electronics and Communication Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India. vishnukumarindian5@gmail.com*

[3] *Department of Electronics and Communication Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India. vasu200210@gmail.com*

[4] *Department of Electronics and Communication Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India. sriragunath.d05@gmail.com*

Volume 6, Issue 14, Aug 2024

Received: 15 June 2024

Accepted: 25 July 2024

Published: 15 Aug 2024

doi: 10.48047/AFJBS.6.14.2024.5120-5130

Abstract-Crop detection is essential for many agricultural applications, such as crop management, crop identification etc. The development of deep learning methods and the availability of satellite imagery have made automated crop detection practical and effective. This work provides a thorough examination and analysis of current advancements in crop recognition utilizing deep learning techniques on satellite imagery. Planning the harvest type can give a premise to separating data on crop establishing design, and region and yield assessment. Acquiring enormous crop type planning by field examination is wasteful and costly. Conventional order strategies have low arrangement precision because of the discontinuity and heterogeneity of harvest planting. In any case, the profound learning calculation has major areas of strength for an extraction capacity and can really recognize and order crop types. This study utilizes GF-1 high-goal remote detecting pictures as the information hotspot for the otherworldly component informational collections are built through field inspecting and utilized for preparing and check, joined with essential review information of grain creation utilitarian regions at the plot scale. The outcomes show that the combination of multi-phantom data and vegetation record highlights further develops order precision. The profound learning calculation is better than the AI calculation in both order precision and grouping impact. Our model proposes a division of the yield over the chose region.

Keywords: Satellite Imaging, CNN, Deep Learning, Crop Detection, Computational Efficiency, Crop Field, Classification

1. Introduction

In the always advancing scene of horticulture, the combination of conventional insight with state of the art innovation has become basic for feasible and proficient cultivating rehearses [1]. The combination of, an old arrangement of regular recuperating, with cutting edge profound learning strategies has made ready for a progressive way to deal with crop location and observing. This momentous collaboration bridles the force of satellite symbolism and man-made reasoning to give an extensive and all encompassing answer for accuracy horticulture. Harvest Discovery Utilizing Satellite Pictures use the standards of, a deep rooted Indian arrangement of medication, to grasp the many-sided connections between yields, soil, and ecological elements [2]. By incorporating this comprehensive point of view with the high level capacities of profound learning, we leave on an excursion to rethink how we see and oversee horticultural scenes. Satellite symbolism, with its wide inclusion and high-goal abilities, fills in as the focal point through which we gain remarkable experiences into the wellbeing and essentialness of yields [3]. Profound learning calculations, capable at handling tremendous measures of information, unwind the intricacies of horticultural biological systems, empowering us to recognize designs, foresee results, and settle on informed choices [4]. This interdisciplinary methodology holds the possibility to change crop the executives works on, offering ranchers a device that recognizes crop medical problems right on time as well as gives customized proposals in light of standards [5]. By melding old insight with present day innovation, Harvest Identification vows to introduce another period of manageable horticulture, where custom and advancement amicably coincide to support ranchers, the climate, and worldwide food security.

2. Literature

In investigate burned area (BA) mapping using radar and optical datasets obtained by the Sentinel-1 and Sentinel-2 onboard sensors [6]. Convolutional neural networks (CNNs) are a well-known deep learning technique that have been extensively utilized in recent remote sensing-based studies. By merging active and passive datasets, this multidisciplinary method creates a mapping algorithm that is both comprehensive and independent of cloud cover, greatly improving upon previous approaches that rely on certain types of sensors. Five regions are used in the study to optimize model settings and integrate sensors; five more areas are used to validate results [7]. At the meanwhile, observations from The International Chemometrics Research Meeting (ICRM) [8].

Held in September 2011, in the Netherlands. The increasing attempts to categorize the world's finite wetland resources are highlighted. These efforts make use of a variety of remote sensing classification techniques, including as decision-tree (DT), rule-based (RB), and random forest (RF) classifiers. The accuracy of wetland studies is greatly increased when ancillary data layers are combined with high-resolution satellite images [9]. Deep learning-based tree species categorization is introduced by an author who highlight its advantages over conventional object-oriented techniques that call for human feature selection. The importance of machine learning in simulating human talents is finally covered [10]. They emphasize the machine's capacity to identify things and carry out tasks that are comparable to those performed by humans.

ORIGINAL RESEARCH article, Front. Environ. Sci., 06 October 2022, Sec. Environmental Informatics and Remote Sensing, Volume 10 - 2022 [11]. Because they offer objectivity and transparency, the review procedures provided by Kitchenham and Charters are suitable for our systematic literature evaluation. The initial formulation of the research questions is done in accordance with the review requirements.

The review is carried out using the full PRISMA checklist (prisma-statement.org), and the findings are reported accordingly [12]. The method for searching the articles is created with the purpose of the systematic literature review and the formulated research questions in mind. Developing a successful search strategy involves focusing on the review's core notion rather than a broad concept. If the search term "deep learning" is used alone, it will produce a large number of published publications from different application sectors that are probably unrelated to the review's goal and complicate the search. Redefining the search approach to include "deep learning," "remote sensing," and "crop yield prediction" can lessen the likelihood of straying outside the parameters of the review. In [13] Deep learning techniques have been the subject of a great deal of research since then.

3. Methodology

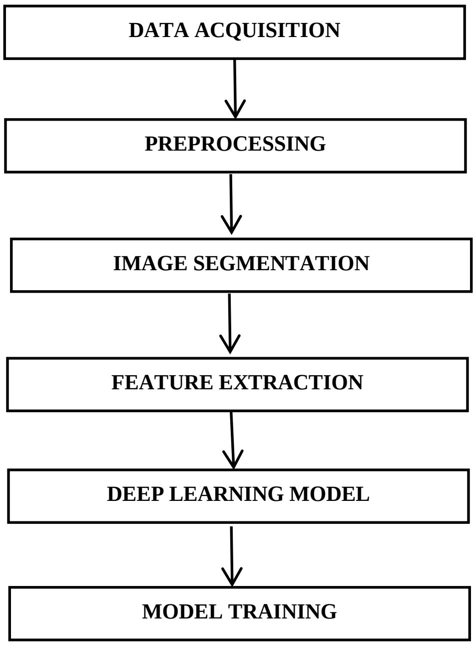


Figure 1. Block Diagram for CNN Implementation

Harvest Recognition Utilizing Satellite Pictures denotes a spearheading crossing point of old rural insight and state of the art innovation, offering an original way to deal with accuracy cultivating. Utilizing the standards of, an old arrangement of regular mending, and the abilities of satellite symbolism, this imaginative philosophy plans to upset how we screen and oversee crops. By integrating bits of knowledge into the investigation of high-goal satellite pictures, the framework tries to recognize unpretentious signs of yield wellbeing and stress. Figure 1 shows the block diagram for CNN Implementation.

This all encompassing methodology considers the interconnectedness of harvests, soil, and natural elements, lining up with standards of equilibrium and concordance in rural environments. The joining of cutting edge picture examination procedures, especially using Convolutional Brain Organizations (CNNs), engages the framework to observe complex examples and settle on informed conclusions about crop conditions. Thus, Yield Location Utilizing Satellite Pictures not just gives a device to early identification of harvest issues yet in addition opens new roads for feasible and careful horticultural works on, blending customary information with the capacities of current innovation.

Modules

Crop recognition utilizing satellite pictures with profound learning includes the incorporation of different modules to accomplish exact and productive outcomes. Here are the key modules normally engaged with such a framework

1) Data Acquisition

Input (remote sensing) datasets of crops, coconut tree and buildings are taken from google earth satellite website. The size of the input dataset image is 1529x925 pixels. Figure 2 shows the image segmentation of Crops.

(a)

(b)

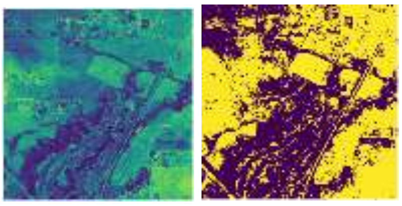
Figure 2. (a) Satellite Image of Coconut Trees (b) Home Areas

2) Preprocessing

Clean and upgrade satellite pictures to work on their quality and make them appropriate for investigation. Information Cleaning handles absent or conflicting information in ground truth datasets.

3) Image Segmentation

There are multiple crucial phases involved in the segmentation of satellite photos for the purpose of identifying houses, coconut trees, and crops. The first step is to obtain high-resolution satellite imagery of the target area and preprocess it to improve features and eliminate noise. Next, choose informative spectral bands or indices to help you differentiate between the various forms of land cover. Figure 3 shows the image segmentation of Crops.



(a) (b)

Figure 3. (a) Image Before Segmentation, (b) Image After Segmentation [14]

4) Feature Extraction

Identifying and defining distinct items or land cover categories within satellite pictures usually entails applying a variety of image processing and computer vision techniques. Here's how you could go about extracting features associated with architecture, agriculture, crops, buildings and coconut palms. Use picture division procedures to isolate crop regions from the foundation in satellite pictures distinguish and remove highlights from the portioned crop regions, like tone, surface, and shape qualities.

5) Deep Learning Model

Plan and train a CNN design for crop characterization in view of the separated highlights. The CNN can learn examples and elements that are characteristic of explicit crops. This model contains three distinct classes such as crops, coconut trees and buildings. It uses Resnet 50 architecture.

6) Model Preparation

Part the dataset into preparing and approval sets. Train the profound learning model utilizing the preparation set and approve its exhibition on the approval set. Model gone through 68 epochs.

4. Existing Work

The calculation of CNN is carried out to portion the area of the given information picture. The Convolutional Brain

Organization (CNN) calculation remains as a foundation in the domain of profound learning, especially famous for its ability in visual information handling. Described by its capacity to consequently learn progressive portrayals, CNNs have upset undertakings like picture acknowledgment, object recognition, and characterization. The engineering of a CNN is intended to emulate the human visual framework, highlighting layers of convolutional and pooling tasks that empower the extraction of unpredictable elements from input information. With its inborn limit with regards to spatial progressive systems, CNNs succeed in catching examples and neighborhood conditions, making them particularly appropriate for picture related undertakings. The use of shared loads and nearby availability lessens the computational weight, working with the preparation of profound organizations. CNNs have demonstrated basic in assorted areas, going from PC vision applications like facial acknowledgment to clinical picture examination and then some. The flexibility and effectiveness of CNNs have moved them to the very front of man-made consciousness, contributing fundamentally to headways in design acknowledgment and data extraction from complex visual information. Figure 4 shows the diagram for CNN layers.

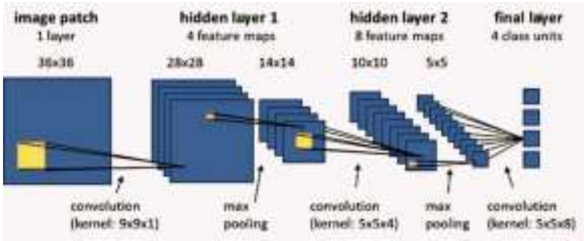


Figure 4. Diagram for CNN Layers [15]

5. Proposed Work

Deep Learning

Profound learning, a subset of AI and man-made reasoning, addresses a change in perspective in how PCs learn and handle data. Motivated by the design and capability of the human cerebrum, profound learning calculations influence brain organizations — refined interconnected frameworks of hubs — to dissect tremendous measures of information and pursue canny choices Figure 5 shows the DNN layers.

At its center, profound learning includes preparing brain networks on huge datasets, permitting the framework to learn complex examples and portrayals. What separates profound realizing is the profundity of these brain organizations, including numerous layers that empower the model to extricate various leveled highlights from the info information consequently. This various leveled highlight extraction enables profound learning models to observe mind boggling examples and connections in the data they dissect.

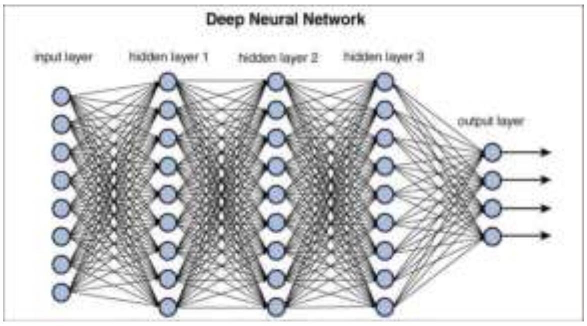


Figure 5. Diagram for DNN Layers [16]

The profound learning upheaval has been energized by progressions in equipment capacities and the accessibility of immense datasets.

ResNet50

A popular convolutional neural network design in computer vision and image processing is called ResNet-50 shown in Figure 6. It is utilized for many applications such as semantic segmentation, object recognition, and image classification. It belongs to the family of ResNet (Residual Network), which is distinguished by the usage of residual connections and a deep structure. This architecture is efficient in filtering, pooling and classifying the input remote sensing images.

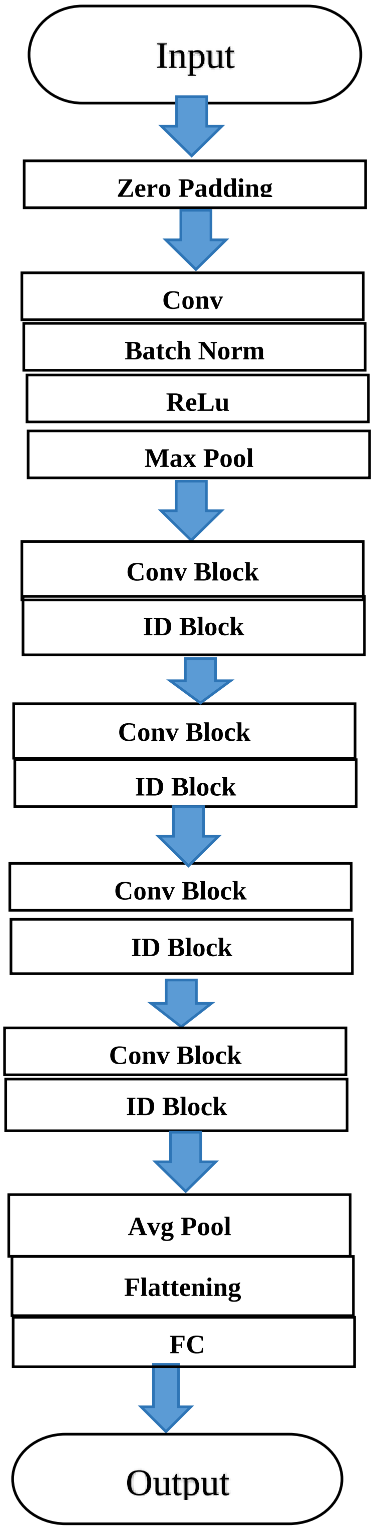


Figure 6. Resnet - 50 Architecture

Confusion Matrix

The confusion matrix is essential for image processing when assessing the success of classification algorithms. By contrasting anticipated and ground truth labels, it provides information on classification errors and accuracy. The matrix can be computed efficiently by using the confusion mat function, where columns represent anticipated class instances and rows represent actual class instances. Figure 7 shows the output confusion matrix value.

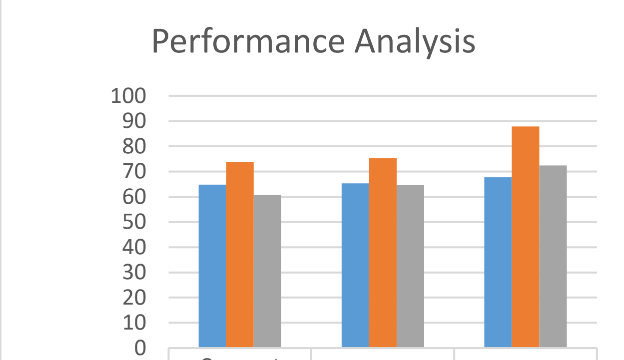
```
confMat =

    0.6000    0.3000
    0.5000    0.4000
```

Figure 7. Output of Confusion Matrix

6. Results and Discussion

A variety of preprocessing techniques can be used to improve the performance of classified remote sensing photos. These methods include picture augmentation, image segmentation, image fusion, geometric correction, and radiometric correction. Improved classification performance is further achieved by using feature selection and extraction in addition to preprocessing. While feature extraction means converting the original characteristics into a new set that is more appropriate for classification, feature selection comprises selecting a subset of features that are especially relevant to the classification task.



	Coconut Tree	Buildings	Crop
Precision	64.77	65.333	67.6667
Accuracy	73.830	75.33	87.83
Recall	60.667	64.666	72.333

Figure 8. Output Analysis of Crop Detection

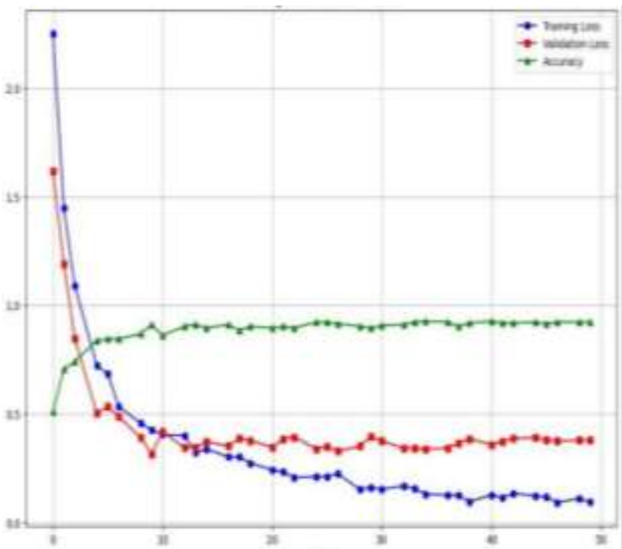


Figure 9. Output Graph for Crop Detection

According to the table and performance analysis shown in Figure 8, the CNN algorithm for coconut tree provides the. Provides the accuracy of 73.83 percentage. Precision of 64.77 percentage and 60.77 percentage of recall. The buildings output, which was compared with existing previous algorithms, gives the result of 75.33 percentage accuracy, 65.33 percentage of precision and 64.66 percentage of recall respectively. The crop, which was compared from another literature review, gives the result of 87.83 percentage accuracy, 67.66 percentage of precision and 72.33 percentage of recall respectively. Figure 9 shows the output graph of crop detection. These results were compared with accuracy precision and recall the parameters was choose to based on the performance analysis from previous existing models. Table 1 lists the accuracy data of the model.

Table 1. Accuracy of Model

S. No	Classes	Accuracy
1.	Crop	87.83
2.	Coconut Tree	73.33
3.	Buildings	75.67

7. Conclusion

All in all, the joining of standards with Convolutional Brain Organizations (CNNs) for crop identification utilizing satellite pictures addresses a groundbreaking step toward reasonable and informed horticulture. This inventive methodology consolidates the old insight of with the high level capacities of profound getting the hang of, offering a comprehensive answer for exact harvest checking. From the perspective of CNNs, the framework proficiently unravels perplexing examples in satellite symbolism, giving a nuanced comprehension of harvest wellbeing and stress in arrangement with standards. The collaboration between experiences and CNN-based picture investigation works with early identification of issues as well as lays the basis for an amicable conjunction of customary rural insight and present day innovation. The CNN calculation, with its capacity to consequently learn various leveled portrayals, arises as an incredible asset in this interdisciplinary undertaking, improving our ability to pursue informed choices and introducing another time of smart and reasonable yield the executives. As Yield Identification Utilizing Satellite Pictures keeps on advancing, its capability to add to worldwide food security and earth cognizant cultivating rehearses is both promising and significant.

References

[1] Pekkeriet, Erik & Van Henten, E.J. & Campen, J.B. (2015). Contribution Of Innovative Technologies to New Developments in Horticulture. Acta Horticulturae., 45-54.

10.17660/ActaHortic.2015.1099.1.

[2] Sayago, S. & Bocco, Monica. (2018). Crop yield estimation using satellite images: Comparison of linear and non-linear models. Agri Scientia., 1. 1. 10.31047/1668.298x.v1.n35.20447.

[3] Peter K. Hargreaves, Gary R. Watmough, Satellite Earth observation

to support sustainable rural development, International Journal of Applied Earth Observation and Geoinformation, Volume 103, 2021, 102466, ISSN 1569-8432.

https://doi.org/10.1016/j.jag.2021.102466.

[4] Rai, D & Kalita, H. & Borah, Dr. (2024). Emerging Trends in Agricultural Extension Education (Volume 2) Chief Editors Dr. Sayanika Borah Associate Editors SP Publishing.

[5] Mohd Javaid, Abid Haleem, Ravi Pratap Singh, Rajiv Suman, Enhancing smart farming through the applications of Agriculture 4.0 technologies, International Journal of Intelligent Networks, Volume 3, 2022, Pages 150-164, ISSN 2666-6030.

https://doi.org/10.1016/j.ijin.2022.09.004.

[6] Pepe, A. & Sali, Matteo & Boschetti, Mirco & Stroppiana, Daniela. (2022). Mapping Burned Areas from Sentinel-1 and Sentinel-2 Data. 62.

10.3390/environsciproc2022017062.

[7] Irfan Younas, Ameera Naeem, Optimization of sensor selection problem in IoT systems using opposition-based learning in many-objective evolutionary algorithms, Computers & Electrical Engineering, Volume 97, 2022, 107625, ISSN 0045-7906,

https://doi.org/10.1016/j.compeleceng.2021.107625.

[8] Leardi, Riccardo. (2003). Chemometrics in Data Analysis. 10.1533/9781855737181.1.299.

[9] Dalponte, Michele & Bruzzone, Lorenzo & Vescovo, Loris & Gianelle, Damiano. (2009). The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas. Remote Sensing of Environment., 113, 2345–2355.

[10] Bayrak, Onur Can & Erdem, Fırat & Uzar, M. (2023). Deep Learning based Aerial Imagery Classification for Tree Species Identification. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. XLVIII-M-1-2023. 10.5194/isprs-archives-XLVIII-M-1-2023-471-2023.

[11] Original Research article, Front. Environ. Sci., 06 October 2022, Sec. Environmental Informatics and Remote Sensing, Volume 10 - 2022 https://doi.org/10.3389/fenvs.2022.991173

[12] Liberati, Alessandro & Altman, Douglas & Tetzlaff, Jennifer &

Mulrow, Cynthia & Gøtzsche, Peter & Ioannidis, John & Clarke, Mike & Devereaux, P.J. & Kleijnen, Joseph & Moher, David. (2009). The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration. Journal of clinical epidemiology. 62. e1-34. 10.1016/j.jclinepi.2009.06.006.

[13] Chandra, Mayank & Bedi, Sarabjeet. (2018). Survey on SVM and their application in image classification. International Journal of Information Technology, 13.

10.1007/s41870-017-0080-1.

[14] Wang, Eric & Wang, Fan & Kumari, Saru & Yeh, Jyh-haw & Chen, Chien-Ming. (2021). Intelligent monitor for typhoon in IoT system of smart city. The Journal of Supercomputing, 77. 10.1007/s11227-020-03381-0.

[15] Timilsina, Shirisa & Sharma, Saroj & Aryal, Jagannath. (2019). Mapping urban trees within cadastral parcels using an object-based convolutional neural network. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. IV-5/W2. 111-117. 10.5194/isprs-annals-IV-5-W2-111-2019.

[16] Zrara, Lamiaa. (2021). Portfolio optimization using deep learning for the moroccan market.