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Deforestation Detection Using CNN- A Review

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ABSTRACT—Without trees and plants, we could not survive. One significant natural resource is forests. For the ecosystem and for our varied needs, forests are essential. They provide everyone on the planet with gasoline, food, and medical supplies. These days, deforestation is one of the world's most pressing issues. It has negligible effects on the climate and ecology. Since the 1960s, more than half of the tropical forests on Earth have been destroyed. Deforestation early detection has become important. Convolutional neural networks (CNNs) are used in deforestation detection to determine the extent of deforestation by using pre- and post- deforestation satellite images as input. Globally, large- scale deforestation results in substantial losses. The rate of deforestation worldwide is approximately 10 million hectares of forest every year. Since 1990, the area covered by primary forests worldwide has decreased by more than 80 million hectares. For a variety of causes, people have cleared woods. Urbanization, mining, illegal logging, and agricultural growth are a few of the factors that continue to fuel deforestation worldwide. Systems based on Convolutional Neural Networks (CNNs), Data Augmentation, Geospatial Analysis and Post-processing Techniques which could involve filtering out small isolated detections, smoothing boundaries, or incorporating contextual information to improve the overall accuracy of deforestation identification have been developed by numerous researchers. Detecting and forecasting deforestation in the agricultural sector requires the application of appropriate image processing and machine learning techniques.

KEYWORDS – Deforestation Detection , Satellite, SVM (Support Vector Machine), Deep Learning, Remote Sensing.

I. INTRODUCTION

One significant natural resource is forests. In addition to providing for our many needs, forests are essential to the environment. They provide everyone on the planet with wood, food, and medical supplies. One of the several ecological, social, and economic effects of deforestation is the reduction of biological diversity [1,2]. Globally, land-use change is the second-largest source of greenhouse gas (GHG) emissions; deforestation accounts for 24 percent of GHG emissions worldwide[29]. The rate of habitat loss in these and other biodiversity hotspots is unknown, despite the widespread belief that tropical regions are losing biodiversity at previously unheard-of rates[23, 24].Although the classification is rough, it is true that the Forest Survey of India (FSI) publishes information on forest cover every two years and has started to give limited data for changes in forest cover in recent years. For instance, it is difficult to distinguish between natural forest cover and tree plantations. Furthermore, distinct data sources and approaches are used to generate the estimates of land cover for the two distinct time periods. A lack of error estimation in the evaluation and the arbitrary division between open and thick forests are two further issues. As a result, the FSI's estimations of forest cover frequently differ from those of other organizations[9]. According to a survey published by the Union of Concerned Scientists (UCS) the bulk of deforestation is caused by four commodities: wood products, palm oil, soy, and cattle [33]. It is true that deforestation can't be stopped if it is not seen.While using conventional techniques is one approach to see deforestation, it is costly and time-consuming to monitor large regions. Satellites are a more useful instrument for tracking deforestation. They quickly capture images of large tracts of woodland. Their archived data over a lengthy period of time allow for the trend analysis of forest cover to guide future decisions. By providing many revisits over the same regions and offering high temporal resolutions, they accelerate the process of detecting deforestation. Landsat and Sentinel satellites give environmental experts an unmatched level of surveillance over the devastation. Choosing the right approach is the biggest problem because there isn't a universal method for identifying deforestation. Therefore further research is necessary. As a result, an extensive survey using cutting-edge machine learning and image processing techniques was carried out.The basic stages of convolutional neural networks are depicted in Fig. 1.1. Our problem's knowledge basis is the detection of deforestation. Preprocessing is done on captured photos to improve the image and eliminate noise or other interference, hence enabling precise detection. Segmentation is an essential phase in the image recognition process since it divides the items of interest for detection. Feature extraction removes unnecessary information from the dataset. In a CNN three common layers are observed: a convolutional layer, a pooling layer, and a fully connected layer[27]. The restricted area of the receptive field is represented by one matrix, which is the set of learnable parameters also referred to as a kernel, and the convolutional layer conducts a dot product between them.. The subsequent pooling layer contributes to the reduction of the representation's spatial dimension, which lowers the quantity of computation and weights needed. As with a typical fully connected layer (FCNN), neurons in the completely connected layer are fully connected to all neurons in the layer before and after them[39]. This connectivity allows calculation using the standard method of matrix multiplication and bias effect. In essence, neural networks are either encoders, decoders, or a mix of the two. The generated data consists of descriptive information or new examples. Several researchers have proposed various techniques for machine learning algorithms, including CNN, SVM, and DL [14]. Machine learning methods are effective for identification in a laboratory environment with a backdrop that is constant. Only recently have machine learning techniques for analyzing satellite data gained traction, despite numerous attempts in the past. With the advancement of satellite imaging, deforestation may now be detected morequickly, easily, and accurately than in the past[25]. Among DL algorithms, the convolutional neural network (CNN) stands out as a top architecture. Unlike conventional ML methods for inference, CNNs use convolutional filters to identify patterns within an n-dimensional context with different abstraction levels. Using remote sensing imagery has been crucial in monitoring deforestation[12]. The National Aeronautics and Space Administration (NASA) defines remote sensing as "the acquiring of information from a distance via remote sensors on satellites and aircraft that detect, and record reflected or emitted energy aiming to "enable data-informed decision making based on the current state of our planet". It uses an economical approach to obtain a wider range of data, particularly in remote locations. Furthermore, by producing spatial maps that act as visualizations and aiding in outlining the extent of damage, remote sensing has proven to be a very suitable method for representing the state of the forests[14]. This paper reviews various deforestation detection techniques and discusses them according to various characteristics. The paper is organized into the following sections. The first section gives a quick summary of the importance of deforestation detection. The techniques used are reviewed and recent research in this area is discussed in the second section. Section 3 reports about the challenges occurred while developing the system The fourth section concludes this paper by outlining future directions. Section 5 is the list of references.

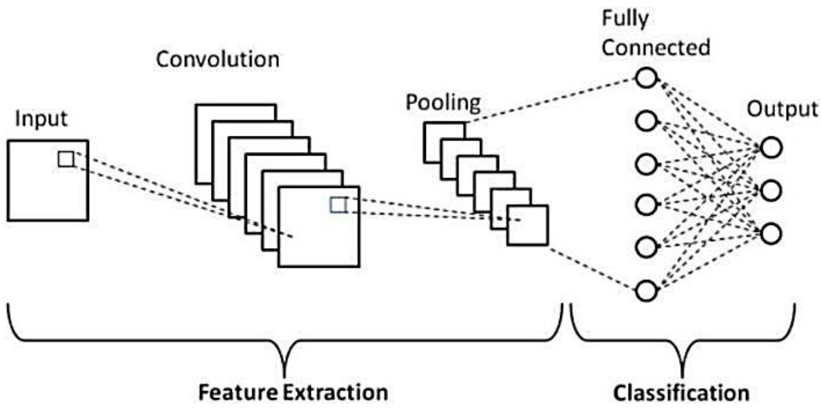

Figure 1: Fundamental steps in convolutional neural networks (adapted from Pranshu,2023)

II. LITERATURE SURVEY

Deforestation, biodiversity loss, and habitat degradation are the results of increasing environmental stresses. exhaustion. As a result, assessing how forested landscapes are changing can shed light on how natural resources are extracted and, consequently, how human activity affects the services provided by forest ecosystems. Reddy et al. [1], examined the rates and causes of deforestation in India and provides an overview of government forest conservation activities. Additionally, it explored the net and gross rates of deforestation at both the local and national levels. Due to the realization of its importance in global warming, biodiversity, and carbon sequestration, forest monitoring has earned significant respect on a global scale. The development of GIS and remote sensing technologies has made it feasible to track and evaluate both net and gross changes in forest ecosystems. Every two years, the Forest Survey of India conducts mapping of the country's forest cover. Compared to the global average of -0.6%, India's current estimate of gross deforestation for the 2009–2011 period is remarkablylow (-0.43%). Despite significant progress in forest protection, the primary obstacle remains the gross deforestation rate Ravindranath et al. [2], aiming to support nations facing extensive deforestation and forest degradation, highlight the role of the Cancun Agreement on the REDD mechanism. The reduction of emissions from deforestation and forest degradation (REDD+) is considered a crucial climate change mitigation strategy. According to the report, deforestation and forest degradation are currently occurring in India. Studies indicate that the effects of climate change are already being felt and will probably get worse in the near and medium future. The objective of the REDD+ mechanism is to provide monetary rewards for curbing deforestation and degradation of forests. Despite having strong laws, regulations, and remote sensing capabilities, India is not prepared to take advantage of the new REDD+ mechanism, which might provide significant financial advantages to populations who depend on forests and rural areas from foreign funding sources Renan Bides et al. [3], presented a new technique for change detection in multitemporal SAR images. It involves the simultaneous calculation of X- and band SAR images to create a binary mask, or change detection indicator image, based on the coherences between all the images used as attributes computed from superpixel segments to define a change detection neural network. Real SAR data from Bradar in the Amazon Forest (Equatorial Rain Forest), collected by the aerial sensor OrbiSAR-2, was used for the experimental tests. The results demonstrated high-quality detections. Renthlei et al. [4], gave an injunction to stop engaging in such barbaric behavior, they warned the young people about the environmental consequences of their activities and the potential legal repercussions for engaging in such behavior. There have been instances where environmental non-governmental organizations discovered young people using slingshots for hunting in rural 200 areas. It is noteworthy that the environmental NGOs' conversations were judged to be quite beneficial, leading to the youths' surrender of several slingshots and their promise to stop engaging in such acts of hunting. An further noteworthy accomplishment of the Environment and Forests Department's and ASEP's awareness programs is that fervent hunters turned in their firearms after realizing the negative impacts of killing wildlife. Sboui et al. [5], aimed to identify the locations in the study where tropical forests have recently given way to oil palm because this may help predict potential future deforestation hotspots. In addition, they want to know where future deforestation might affect biodiversity the greatest. The suggested approach is based on an evaluation of a collection of parameters associated with this kind of deforestation and a conceptual framework. A sensitivity analysis is used to evaluate and validate the criteria. Machine learning and image processing algorithms provide the foundation of the system. The three primary phases are data preparation, model training, and validation. Saha et al. [6], used five distinct machine learning methods, this study aimed to detect the deforestation probable zones of Jaldapara National Park and its environs (SVM, NB, RF, DT and ANN). According to the findings, widespread human encroachment, poaching, and timber trafficking are to blame for the high rate of deforestation in the northern and middle sections. The outcome also shows that, in comparison to other models, the support vector machine (SVM) brings better accuracy. Pratiwi et al. [7] created a CNN model used to categorize the eight kinds of land cover using satellite photos. Identifying deforestation early was one of the goals of the project. The study contrasted the Alexnet architecture with a basic CNN with four hidden layers as training models. This study also looked into training factors like learning rate, batch size, epoch, and input size. With a loss of 0.56 and validation accuracy of 90.23% across 100 epochs, the Alexnet design performed well. CNN's four hidden layer validation technique yielded the best results, with 95.2% accuracy and a 0.17 loss. Hosonuma et al.[8], sought to change the way forest activities are trending in order to achieve a more biodiversity- and climate-friendly result. In the process of creating national policies and action plans for REDD+, countries are urged to pinpoint the causes of deforestation and forest degradation. Through the synthesis of empirical data given by countries as part of their REDD+ preparedness operations, CIFOR country profiles, UNFCCC national communications, and scientific literature, they gave an assessment of proximal drivers of deforestation and forest degradation in this research. Countries were divided into four forest transition stages based on the rate of deforestation and the amount of surviving forest cover. Subsistence farming comes in second as the main cause of deforestation, after commercial farming. The majority of the degradation is caused by logging and the extraction of timber, which is followed by the production of charcoal and fuelwood, uncontrolled fires, and livestock grazing. Dutta et al.[9], estimated how the forest cover in the southern Western Ghats changed between 1973 and 1995. One of the numerous ecological, social, and economic effects of deforestation is the decline in biodiversity. Two of the 24 hotspots for biodiversity in the world are located in India: theWestern Ghats and the Eastern Himalayas. The rates of deforestation and changes in land use vary significantly throughout regions. The current time is estimated to have seen the highest levels of deforestation in the region ever recorded. Data was gathered from MSS and LISS 1. The final mapping was found to be 80%. The high rate of deforestation shown here does not account for habitat fragmentation and further deforestation, which eventually result in the loss of forest protection. Pasha et al. [10], used Landsat-8 data and an integrated spectral enhancement approach to study the Northeastern Indian region's shifting agriculture fallow/current jhum area. Through field sampling, the native vegetation on fallow land under shifting cultivation was examined. Northeastern India's unique biodiversity has been threatened by shifting farming (Jhum).In this research, the largest amount of land left for shifting agriculture was in Manipur state, while Tripura state had the least amount. The state of Arunachal Pradesh ranked highest on the shifting cultivation fallow hotspot map, which was created to locate the recurrent. spots. In less than three years, old shifting cultivation fallow fields provided insight into the dynamics and vegetation composition of shifting cultivation fallow lands. Although the tendency has started to decline, shifting agriculture remains a threat to Northeastern India's fragile ecosystems, according to a study conducted using a remote sensing approach. The quality of land use management plans could be improved by routinely updating the database created in the future with more recent Sentinel-2 data with greater geographical and temporal resolution. Jha, et al. [11], highlighted the deforestation played by factors related to perceptual processes of economic and social change, including unequal land distribution, commercialization of agriculture, land loss, and poverty. The deforestation trend has also been supported by other factors like land speculation and inflation. However, the paper makes the case that the government's development strategy over the previous three decades, which allowed for the establishment of large-scale agricultural and cattle-raising schemes through credit, taxation, and other incentives, is primarily to blame for the majority of the massive deforestation. Deforestation has also been exacerbated by the support of mining and hydropower projects in the Amazon and by initiatives to boost exports in order to pay off the massive external debt. The article emphasizes that an analysis of Amazonian deforestation must take into account Brazil's entry into the global economy and overall growth model. Solorzano et al. [12], measured and monitored using remote sensing. Deforestation contributes to climate change by reducing biodiversity, increasing atmospheric carbon emissions, and deteriorating ecosystem services. Monitoring deforestation has become easier with the advent of deep learning techniques and higher spatial and temporal resolution satellite photography. This study uses multi- aperture radar pictures to assess the possibility of using space storm research to intensify Southeast Mexico. This study's major goal is to assess the accuracy of the CNN-based DL approach, specifically the U-Net 3D architecture, in identifying two forms of deforestation: primary forest loss and secondary forest/afforestation, utilizing both MS and SAR pictures. Classification problems were discovered in the group's location, either as a consequence of artifacts in the image or as a result of conflict between the loss of grass cover and secondary forest/plantation. J.G. Ball et al. [13], demonstrated how deep neural networks can pick up spatiotemporal patterns of deforestation from a small collection of publicly available worldwide data, such as many satellite photos, Hansen historical deforestation maps, and ALOS JAXA digital surface models. Because of the intricacy of the natural and human processes involved, estimating the extent of deforestation is challenging; nonetheless, early and precise estimates can result in efficient planning and management. With ever-growing volumes of real-world observation data, new deep learning-based computer vision algorithms can be used to produce previously unheard-of insights and forecasts with unparalleled precision. Based on 2D CNN and 3D CNN, they created four deep learning models. Over the course of the following year, retrieval risk design will be based on 3DCNN, long-term memory (LSTM), and RNN for each forest pixel (~30 m) in the landscape. They used data from a southern Amazonian rainforest for training and testing. Governments and conservation organizations employ this strategy, which is easily applicable to all forest areas, to prepare protected areas and stop deforestation. Ortega et al. [14], investigated how to assess satellite imagery and identify changes in land cover using a variety of deep learning models, such as CNNs and RNNs. The study starts out by discussing the difficulties in detecting deforestation, namely how big and far-flung the Amazon forest is. The study's findings demonstrate how well deep learning methods can recognize patterns of deforestation in the Amazon rainforest. De Bem et al. [15], detected deforestation in the Brazilian Amazon by comparing photos taken at various points in time to determine the locations of deforestation. Three distinct Deep Learning architectures were used in this study: ResUnet, SharpMask, and U-Net. Two traditional machine learning techniques, random forest (RF) and simple multilayer perceptron (MLP), were also employed in addition to the DL algorithms. Because they are machine learning-based, these algorithms are comparable. According to the study, Deep Learning algorithms outperform conventional algorithms by a wide margin. Lee et al. [16], used deep learning algorithms and high-resolution remote sensing data to investigate the classification of landscapes, such as mountainous areas damaged by deforestation in the Korean forests. The Kompsat-3 satellite provided high-resolution remote sensing data that was used to select the study regions that had experienced recent deforestation. The segmentation data that was created to include geographic attributes was used to gather the datasets for deep learning. The accuracy of the classification of the forest and non-forest areas was as high as 98.4% and 88.5%, respectively. The classification of non-forest land cover, which includes fields, roads, buildings, and grasslands, was not very accurate. Kumar et al. [17], used a logistic regression model (LRM) to identify and forecast the changes related to the conversion of forests. The study region was the Kanker district of Chhattisgarh, India's Bhanupratappur Forest Division (19°42′02′–20°13′32′ N and 80°24′11–81°23′44′ E). The chance of a forest change was predicted and the relative importance of the explanatory variables was evaluated using logistic regression. In order to develop a logistic model, they investigated the effects of five independent variables on forest conversion: topography, soil texture, land tenure, and distance from roads and settlements. Between 1990 and 2010, the region's changes in forest cover were accurately predicted by the LRM. Better conservation and management techniques are made possible by this research's contribution to our understanding of the variables influencing forest conversion in the Bhanupratappur Forest Division. Muller et al. [18], studied from 2011 to 2017 and evaluated the amount of rainforest cover in a particular area of north- western Paraguay using satellite imagery from LandSAT5, LandSAT7, and LandSAT8. MATLAB software was used to process these pictures and produce a 3D matrix. Coordinates on the x and y axes were allocated to every pixel, and the RGB color intensities ranged from 0 to 255. The outcome for each pixel was predicted by the researchers using a regression technique, and the RSME (root mean square value) was used to assess the accuracy of the regression line. Their research showed that the rate of deforestation grew faster than predicted by a 2nd order polynomial curve throughout the past ten years, especially in 2010. Saha et al. [19], predicted portable zones of deforestation using remote sensing and machine learning. The Gumani River served as the study area. The Gumani River Basin (GRB), which spans an area of 1274.57 km2, is primarily situated in the eastern Indian state of Chhotanagpur plateau periphery, between latitudes 24°37′39 N and 25°7′19 N and longitudes 87°21′20 E and 87°54′20 E. K. Lavanya et al. [20], presented a new method for detecting land cover change and land use change in India's Nallamala Forest called the Tunicate Swarm Algorithm with Deep Learning Enabled Land Cover Change Detection (TSADL-LULCCD). For feature extraction, the TSADL-LULCCD method uses a dense EfficientNet model. This method uses the Deep Belief Network (DBN) approach to categorize land cover. The Nallamala region's LANDSAT-7 satellite pictures were used in the investigation. In this study, a Deep Belief Network (DBN) was specifically used for land cover classification.

III. CHALLENGES

- CNNs, which are extensively utilized for tasks like image classification, object detection, and even land cover change detection, require high-quality labeled data in order to be trained efficiently. For these networks to identify patterns and generate precise predictions, a sizable and varied dataset is necessary.
- Variations in image quality and inconsistent data sources can have a major effect on CNN model performance. These problems might cause noise and hinder the network's ability to identify significant patterns. It is possible to use different sensors, cameras, or platforms to record data from various sources. variances in these variables may result in variances in image properties like color balance, resolution, and distortions. Reducing sensor-related fluctuations can be

achieved by using preprocessing techniques such as color normalization or histogram matching. Furthermore, transfer learning can aid in adapting to various data sources by refining previously trained models on the target domain.

- One major hurdle that might negatively impact the performance of machine learning models, such as CNNs and other classification techniques, is the class imbalance problem in deforestation detection datasets. The machine learning model becomes biased towards the majority class (in this case, non-deforested areas) when it is faced with imbalanced datasets. As a result, the model might not be able to identify deforestation well enough since it lacks sufficient samples of the minority class to workwith.
- The construction of machine learning models for tasks like picture segmentation can be especially difficult because a significant amount of training data is required, in addition to the specific hardware requirements for training. Making accurate ground truth masks is a major issue in this procedure, particularly for targets that are specific to photographs. Because it requires a thorough comprehension of both spatial and spectral settings, this task becomes hard. It takes a lot of time andeffort to create ground truth masks that faithfully capture the desired features in photos, especially when working with large geographic areas. For the purpose of locating and dividing particular items or areas of interest within the photos, the combination of spatial and spectral context is essential.
- In order to prepare satellite imagery for CNN input, it frequently needs to undergo intensive preprocessing, including picture registration, cloud removal, and normalization. Preprocessing like this might take a lot of time and computing power.
- Another issue with the CNN structure is that it just conveys the likelihood that an object of interest will appear in a picture; it does not offer information about the object's precise location or spatial coordinates.

IV. CONCLUSION

To sum up, the amalgamation of deep learning and machine learning technology has resulted in a significant advancement in deforestation detection systems. For image analysis, the conventional machine learning techniques provide a more efficient method. They can generate findings that are passably good even with much smaller sample sizes and more straightforward sampling designs. Their effectiveness may render them a more viable option for assignments that present considerable obstacles in terms of ground truth annotation and large- scale data collection.The yearly changes in the vegetation cover that were detected using the DL architectures demonstrate that these algorithms are a good substitute for classical ML algorithms, improving all performance metrics and having definite benefits like shorter prediction times and less noise in the classifications. While the ML models demonstrated a clear loss of quality in more difficult-to-classify patches, with a propensity to produce false-negatives and impulse noise that required filtering, the DL methods also produced classification masks with clearly identifiable deforestation areas. With its capacity to collect and process information from a distance, RS has emerged as an indispensable instrument for tracking and identifying deforestation activities. In the current world, topographic maps are essential for science, research, planning, and administration. It is quite possible to identify changes using RS data that was gathered at two different times. Specifically, CNNs are deep learning algorithms that show great potential for accurately identifying and classifying deforestation from image data[7,30]. Since these models can learn hierarchical representations directly from raw pixels, they do not require hand-crafted features.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest

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