Stopping The Silent Saw: How CNNs and Satellite Data can Revolutionise Deforestation Monitoring

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Abstract:

Deforestation in the Amazon Basin contributes the largest share to the Overall Deforestation. An approximate area of 48 Football Fields is wiped out every Minute. This has resulted in the loss of habitat, Climatic Changes, increase in overall temperature, etc. Improved data regarding deforestation and human encroachment in forests can enable governments and local stakeholders to react with greater speed and efficiency. Early detection allows authorities to implement stricter regulations and conservation efforts. By using satellite imagery, this project contributes to a larger goal of sustainable forest management, reducing the pollution caused by deforestation and ensuring a healthier planet for all. To combat deforestation effectively, usage of a robust model such as Convolutional Neural Networks as a powerful deep learning algorithm allows image recognition and classification to assess land cover types and monitor the air quality in the aerial imagery of the Amazonia. By tracking the images in this vast rainforest over time, the aim is to train a model to automate deforestation monitoring so that it highlights and alerts in advance to take measures and combat the problem of climate changes. By achieving the objective of land cover classification and deforestation probability mapping, this project aims to provide a valuable tool for environmental monitoring and contribute to the fight against deforestation.

Problem Statement:

Deforestation poses a critical threat to our planet's health, contributing to climate change, air pollution, and biodiversity loss. To combat this issue, we propose the development of an automated system that utilises satellite imagery to detect and monitor deforestation. By harnessing neural networks, we aim to provide timely and eye-catching insights into forest degradation, empowering stakeholders to take proactive measures to protect our environment.

Objectives:

1. To ascertain the labels of the images and carry out dehazing.

2. Employ statistical methodologies to establish predictive models for deforestation detection and pollution probability, aiding in the formulation of targeted conservation efforts.

3. Investigate the interplay between deforestation and carbon emissions, illuminating the ecological ramifications and guiding effective mitigation strategies.

Introduction:

Forests are not just trees; they are the breathing heart of our planet.

Consider a Jigsaw Puzzle, what if someone takes out a piece and does not put it back. Now Consider this puzzle to be a Big Forest, and pieces of the puzzle being each Tree which are present there. Will the Puzzle be Complete without the Trees? Exactly that's the Simplest way to understand what Deforestation is. Cutting Down each tree in the Forest is like removing every piece of the puzzle one by one. With time when the time comes wherein you have reached an extent to which you can remove these pieces, you will start facing Big Problems. This a Lose-Lose situation for us. To address the issue of deforestation, we need to look at What causes Deforestation? And What are the Reasons behind it?. When Forested land is purposefully cleared to increase the availability of land for various reasons such as Agriculture, Constructions, etc. It is called Deforestation. But not always this Deforestation is caused by direct human interference. Sometimes, indirect human interference can also lead to Deforestation. The Pollution caused by human beings is also an indirect way resulting in Deforestation. Deforestation has always been a problem since last few centuries.[2] With the increase in human population in the last few centuries, this problem has escalated to another level. If the growth of population continues at the same rate, there will be more demand for land to settle them. This Deforestation will have negative impacts on the Environment. In recent years, awareness of the negative impacts of deforestation has increased, prompting efforts to protect and restore forests.

The Amazon is considered as the lungs of the planet which helps to stabilise the planet's climate and global warming by absorbing CO_2 and producing O_2. Forests help to attenuate the effects of climate change. Deforestation takes a toll on the efforts of the forests by working in a direction opposite to it. Deforestation serves as a critical threat to Earth's ecosystem and biodiversity as well. Several species of animals and birds are native to a region and clearing those lands pose a grave danger to those species and inch them closer to being classified as endangered or extinct. The Native Species are also Impacted by the Climatic and Temperature change caused by Deforestation. This has also changed the Climate of areas which have impacted the Habitation living there. It is one of the pivotal causes of loss of biodiversity, climate change and reducing it is of prime importance and works in the best interest of the planet. Deforestation does not just affect forests and animals; it impacts humans too.[3] When trees are cleared, it disrupts the balance of oxygen and carbon dioxide in the air, making it harder for humans to breathe. The Chances of Floods and Landslides also increases with the increase in Deforestation. It also Causes Soil Erosion resulting in loss of nutrients present in the Soil. This Soil Erosion in turn poses a problem to Human Beings. The implications stated above are some serious risks to humans. Additionally, it reduces the availability of natural resources like wood and clean water, which communities rely on for survival.

This project aims to address deforestation by monitoring it over time. It's not just about identifying where trees are being cut down; it also looks at the reasons behind deforestation. This information plays a vital role in developing strategies relating to combat deforestation and mitigation of its environmental consequences. With rapidly increasing climate change threats, our goal is to understand the and evaluate the effects and the pre-eminence of deforestation to highlight its sensitivity in environment preservation.

Literature Review:

On accentuating the deep learning computing paradigm, in "*Review of deep learning: concepts, CNN architectures, challenges, applications, future directions (Alzubaidi, Laith, Jinglan Zhang, Amjad J. Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, José Santamaría, Mohammed A. Fadhel, Muthana Al-Amidie, and Laith Farhan | (2021))"* has achieved results on complex cognitive tasks using convolutional neural networks. By using CNN features such as AlexNetwork and High-Resolution network, the paper indicates ways to improve the performance of the architecture of the fully connected network. By evaluating the effectiveness of deep learning architectures and highlighting its potential benefits for automating deforestation monitoring.

Mapping the deforestation is an essential step in the process of managing tropical rainforests as reflected in *"Change detection of deforestation in the Brazilian Amazon using landsat data and convolutional neural networks(De Bem, Pablo Pozzobon, Osmar Abílio de Carvalho Junior, Renato Fontes Guimarães, and Roberto Arnaldo Trancoso Gomes | 2020)"* which allows us to understand and monitor the implications of such causes by using deep learning algorithms, particularly convolutional networks. CNN aids in examining annual variations in vegetation cover within Brazilian forest regions. These structures underscore a distinct advantage over traditional machine learning models, both in terms of quantitative analysis and visual representation when mapping deforestation.

Presently, there is significant research emphasis on utilizing Convolutional Neural Networks (CNNs) to identify deforestation from satellite images as mentioned in **"***Using Time Series Image Data to Improve the Generalization Capabilities of a CNN- The Example of Deforestation Detection with Sentinel-2 (M. X. Ortega, D. Wittich, F. Rottensteiner, C. Heipke,R. Q. Feitosa | 2023")* CNN delivers less desired results when applied to new data in the real world. When it is used along with time series-based data, it acquires classifiers that generalise better to new data. The use of time series along with CNN yields results with an improved accuracy as compared to that obtained for a CNN model by utilising temporal information of the images.

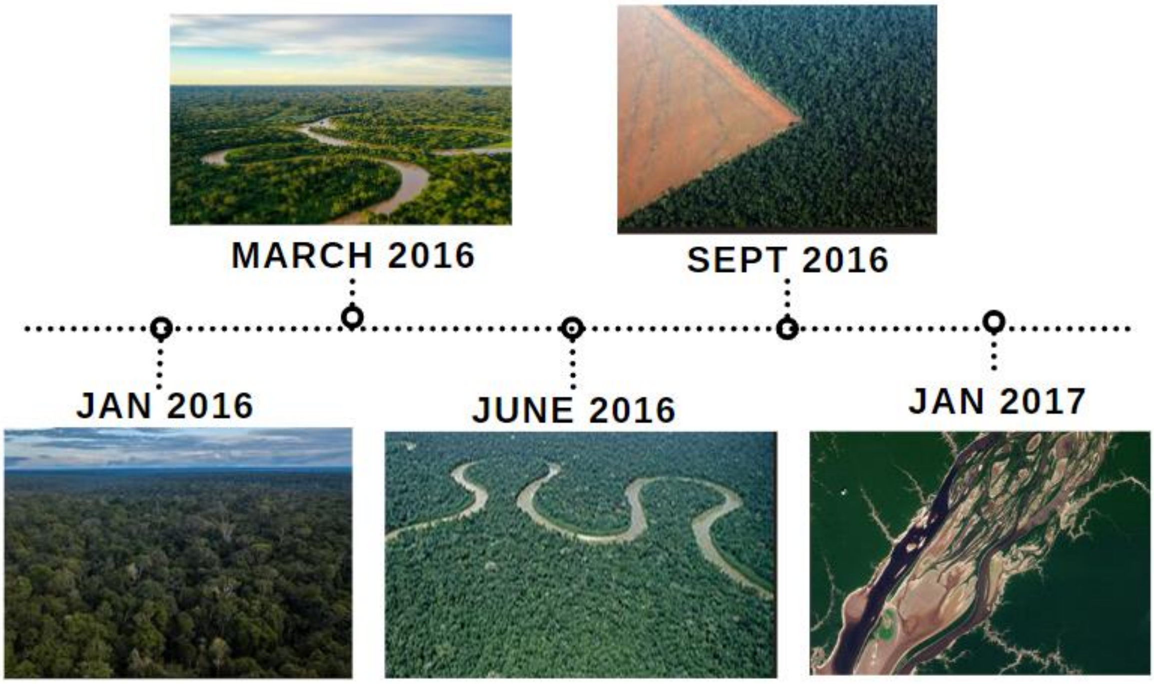
Images captured under varying weather conditions not only exhibit color degradation, diminished contrast and saturation, and inferior visual quality, but also impact the functionality of optical processing-dependent imaging instruments. As highlighted in *"Image dehazing using residual-based deep CNN. (Li, Jinjiang, Guihui Li, and Hui Fan | (2018))"*,[1] physical model-based methods restore the image to be more realistic and closer to pre degradation scenes and applies residual dehazing using the residual network of the CNN algorithm to obtain fog free imagery. This is combined with residual learning to improve the learning speed and thereby obtain results by classification of spatial maps.

Assumptions:

Deforestation is a process that takes place over a period. The dataset that we analyzed is of a one-year period, from January 2016 to January 2017. Since it is a gradual process, analyzing it over a long time period will help to visualize and understand deforestation that occurred in that area if any.

The following five images were tested to check for the occurrence of deforestation in the forest from the period 2016-17.

From the images, it can be noticed that the first image has dense forest which later reduces due to mud slurry in rivers caused due to mining. A vast piece of land has been cleared what appears to be for agricultural purposes, a leading cause of deforestation. The last image hypothesizes that deforestation has relatively reduced since the past period. From the images it can be noticed that initially it was a dense land where deforestation took place over due course of time but the process did move in a positive direction for a while where deforestation was comparatively lower.
To confirm our above assumption, we compared it with the actual data during the same period.



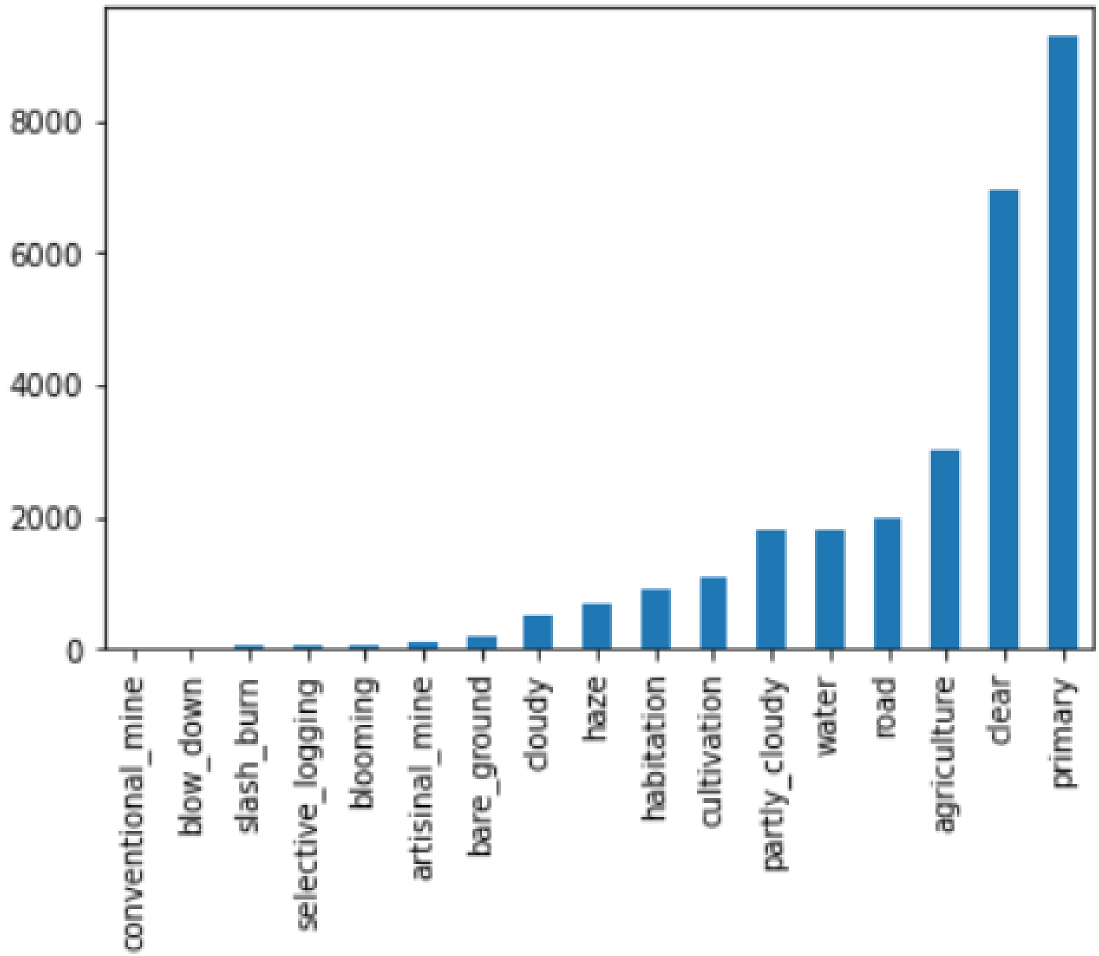
The above pictures confirmed our assumption of the presence of deforestation throughout the year. In these images as well, first a dense forest is seen and gradually the forest cover is getting degraded with time.

Data Collection:

Source: https://www.kaggle.com/c/planet-understanding-the-amazon-from-space
"The data is obtained from a secondary source and is present in the chip jpg format that was derived from Planet's full-frame analytic scene products from the 4-band satellites in sun – synchronous orbit (SSO) and the International Space Station (ISS) orbit. The imagery has a ground sample distance of 3.7m and an orthorectified pixel size of 3m. It was collected between January 1, 2016 and February 1, 2017 covering the horizon of the Amazon basin including Brazil, Venezuela, Ecuador, Peru, Bolivia, Uruguay, Guyana, Colombia and Bolivia." [4]

Data Exploration:

The bar graph below represents the classification of images into different classes. The x-axis portrays the class labels and the y-axis consists of the frequency or the number of images under each class. Multiple labels have been allotted to each image based on its characteristics but a single image cannot be both clear and cloudy for example. Similarly, labels habitation, bare ground, cultivation, and agriculture cannot be allotted to the same image. However, for example, labels clear, primary and cultivation can be dispensed to the same image. Most of the images satisfy the categories clear and primary (over 6000 and all images are primary).



Data Labels:

Cloud Cover

Satellite Imaging can be impacted when Clouds are present. This poses a major challenge which can impact the monitoring of the area. Skies without the presence of clouds are labelled as clear and those with opaque cover visible are described as partly cloudy.

Primary Rainforest

This label is used for any image that has the presence of dense tree cover.

Water

This label is collectively used for all the rivers, reservoirs and oxbow lakes which are present in the Amazon basin.

Habitation

This label is used when the image appears to have the presence of human homes. It contains dense urban centres or dwelling along the river banks in the form of rural villages. It occurs as clumps of pixels that are bright white.

Agriculture

Major cause of deforestation in the Amazon Rainforest is Agriculture.. In this dataset, agriculture is considered as land devoid of trees which in turn is used for agricultural purposes.[5]

Road

Roads are essential for transportation in the rainforest but are also a contributing factor to deforestation. New road construction leads to “fishbone” deforestation which is generally due to population pressure and change in land cover in association with roads and highways. Smaller logging roads are the cause of selective logging. In the dataset, all types are classified as road.

Cultivation

It is a subset of agriculture and hence a driver of deforestation. It is observed in rural areas where farm plots are maintained by people for their livelihood. Small villages are found along the rivers and at the outskirts of agricultural areas.

Bare Ground

It is a naturally occurring area devoid of trees whose result is not a consequence of human activity.

Slash and Burn

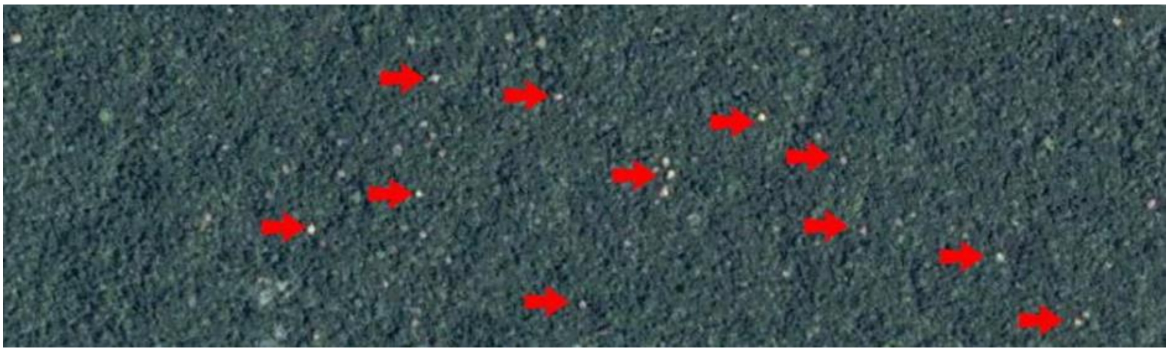
It is a subset of cultivation and another cause of deforestation and pollution. It is a region where cultivation took place and now it is burnt. This can be seen as dark brown or black images in areas classified as cultivation.

Selective Logging

This label is used to cover the practice of selectively cutting high value trees such as teak and mahogany. It is seen as winding dirt roads next to bare brown patches present in an area otherwise categorised as primary rainforest. [7]

Blooming

It is a naturally occurring phenomenon where certain species of trees bloom flowers and fruit at the same time to maximize the likelihood of cross pollination.



Conventional Mining

Though conventional mining is legal, it is another factor leading to deforestation as well as pollution. The label classifies large scale conventional mining operations taking place in the Amazon basin.

Artisanal Mining

This is an illegal activity carried out by all people who are in search of gold in the Andes Mountain. They work on lands otherwise reserved for conservation, cut trees to make a path for them and excavate deep pits near rivers. This leads to deforestation as well as pollution.

Blow Down

This is a naturally occurring event where cold dry air from the Andes settles on top of the warm moist air present in the rainforest. It creates a hole in the warm air and settles down with immense force and speed. These cold high-speed winds knock down the larger trees resulting in an open area. [9]

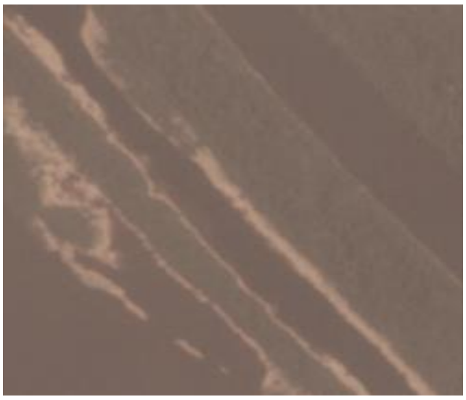
Methodology:

The above data has been filtered to ascertain uniformity among all images by resizing its resolution (256*265 pixels) and split into train and test samples with 10000 images in the train dataset (train-jpg) and 1000 images in the test set (test-jpg). For each image in the train data, there are multiple labels corresponding to it in the train_csv file. The CNN architecture is inspired by the connectivity of the human brain and is predominantly used to process images. It is a deep learning method that breaks down images and leads to pattern formation and recognition based on the pixels of an image.

By using tools like python and exploring libraries such as tensorflow, keras, fastai, opencv among many others, the step-by- step breakdown of the procedure is given below:

1) **Identification of the Problem Statement:** Our Main aim is to highlight the importance of Forests and the Key Role it plays in maintaining the Ecosystem. Therefore, the need of the hour is the efficient Detection of Deforestation to facilitate Strategizing.
2) **Data Collection:** Data has been collected from a Secondary Source which includes images from the Satellite that are cleaned to ensure Uniformity.
3) **Deciding the Mathematical Model to be used:** The Main Aim of this stage is to decide upon the Algorithm which best suits our data to learn the Process Imagery. CNN has been selected due to its Deep Learning Abilities.
4) **Image Classification:** Based on the features of the landforms, the images were labelled separately by using the ResNet50 model of the CNN algorithm.
5) **Dehazing:** Most important step in obtaining accurate results. It is the process of removing haze from the image so as to obtain clearer images which facilitates a smoother learning algorithm.
6) **Modelling:** Application of the CNN model to the dehazed images to train the data by using ResNet50. Probabilities for the levels of pollution and deforestation are then obtained from testing.
7) **Conclusion:** Testing the Accuracy of the model and drawing inference from them.

Presence of haze impairs the clarity and quality of images. It might lead to confusion in the training of the algorithm. In order to overcome this limitation, dehazing plays a key role by restructuring the pixels in these images. The Dark Channel Prior is an input learning-based algorithm where transmission of images is assumed to be constant and the intensity of colour channels is decided after dividing the degradation on both the image and its fragments. The presence of satellite data and high haze levels make DCP a suitable choice to understand the complex structure of the image. It facilitates the usage of low-quality images and enhances the quality which subsequently helps in the correct classification of the labels.



ResNet50 is a special type of convolutional neural network which incorporates the convolutional block attention module (CBAM) which enhances the feature extraction capability making it suitable for robust datasets. Further, it is a fully connected transfer learning method which enables the modifications to accommodate specific tasks, in this case, detection of deforestation without any loss of information.[8] Therefore, the usage of ResNet50 proves to be an ideal model for the analysis over other networks.
Finally, it is important to test the accuracy of these models and its predicted classification values. To evaluate the accuracy, f2 score has been calculated on the test data of the CNN models. The f2 score is the harmonic mean of the precision and recall, given a predetermined threshold value. It gives more weight to recall than precision which evaluates the performance of the classifier and the goal is to balance the precision and recall.

Model Implementation:

Model 1: Dark Channel algorithm

The Dark Channel algorithm is a method used for image dehazing. It works by identifying the darkest areas in an image, which typically correspond to regions affected by haze or fog. By estimating the atmospheric light and haze density, the algorithm removes haze from the image, resulting in clearer and more visually appealing pictures. This process enhances the visibility of details and improves the quality of the image for various applications such as object detection and environmental monitoring.

1. Dark Channel: The dark channel $J^{dark}(x)$ of an image $I(x)$ is defined as:

$J^{dark}(x) = \min_{y\in\Omega(\mathrm{x})}\left(\min_{\mathrm{c}\epsilon\{\mathrm{r,g,b}\}}\left(I^{c}(y)\right)\right)$

2. Atmospheric Light: The atmospheric light A is estimated as the maximum intensity value in the dark channel mathematically:

$A = \max_{x\in\Omega}\left(J^{dark}(x)\right)$ where Ω denotes the set of all pixels in the image.

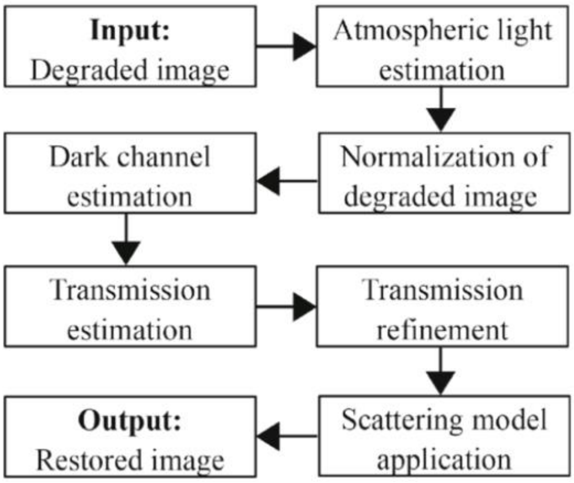
3. Transmission map: The transmission map $t(x)$ describes the proportion of light that travels through the haze at each pixel. It is computed as:

$t(x) = 1 - \omega * \frac{\left(J^{dark}(x)\right)}{A}$ where ω is a parameter to control the strength of the haze removal. Typically, it is set to a value between 0.8 and 0.95.

4. Scene Radiance: Finally, the scene radiance $J(x)$, which represents the haze free image as obtained using the following equation:

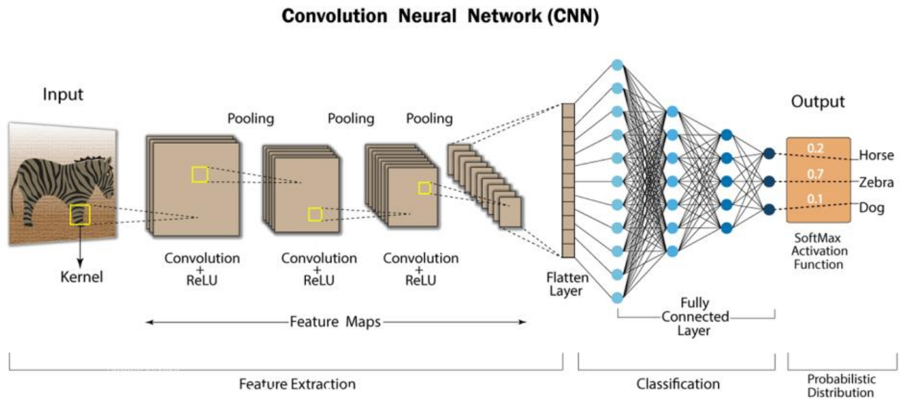
$J(x) = \frac{I(x)-A}{\max(t(x),t_0)} + A$ where t_0 is a small constant to prevent division by zero and $I(x)$ is the input image.

Procedure:



Model 2: Convolutional Neural Networks

In deep learning, CNN is an algorithm used to analyse image and video data. The framework of such structures is based on "features" which are obtained by breaking down the image into specific fragments that facilitate the classification and recognition of objects in the image. In other words, convolutional networks look at the combinations of different pieces of various shapes and colours.
They are basically different layers that focus on various parts of the image step by step to build a feature map by working together in the end which can be used to make inferences about certain parts of the image.



Convolutional Layers:

- Convolutional layers apply filters to the input data, sliding them across the input to perform convolution operations.
- These filters detect features in the input data by capturing spatial patterns like edges, textures, or shapes.
- Each filter generates a feature map that highlights the presence of a specific pattern in the input.
- A single convolutional channel for image I and a filter K can be represented as follows:

$$\boldsymbol{f}[\boldsymbol{i},\boldsymbol{j}] = (\boldsymbol{I} * \boldsymbol{K})_{[\boldsymbol{i},\boldsymbol{j}]} = \sum\sum \boldsymbol{K}_{[\boldsymbol{x},\boldsymbol{y}]} \boldsymbol{I}_{[\boldsymbol{i}-\boldsymbol{x},\boldsymbol{j}-\boldsymbol{y}]}$$

Activation Function:

$\boldsymbol{ReLU}: f(x) = \max(0, x) - Introduces\ no - linearity\ by\ setting\ negative\ values\ to\ Zero.$

$\boldsymbol{Sigmoid}: f(x) = \dfrac{1}{1 + e^{-z}} - Squashes\ the\ output\ between\ 0\ \&1, suitable\ for\ Binary$

$\boldsymbol{Softmax}: f(x_i) = \dfrac{e^{x_i}}{\sum_j e^{x_j}} - Converts\ the\ output\ into\ probabilities, often\ used\ for\ multi - class$

$\boldsymbol{Linear}(\boldsymbol{Identity}): f(x) = x - Passes\ the\ input\ through\ unchanged, used\ in\ regression$

The next step is to pool the layers that take the output from the convolutional layer and down sample it by selecting a metric that enables the reduction in size of the feature map and prevents overfitting. This output is then fed into a fully connected layer which performs the final classification or prediction. The features learned from previous layers are manoeuvred to set an output or obtain class values. Thus, CNN uses the concept of backpropagation where the weights of neurons are adjusted to minimise the error in the test data.

Model 3: Resnet50

- ResNet50 is a type of CNN model that introduces the concepts of residual learning in order to address the challenges of training extensively deep neural networks. Its input layer receives raw data, typically that of images where multiple convolutional layers are applied just like CNN where, in a ResNet50 network, a specific architecture is designed to apprehend complex features.[10]
- Residual blocks are then formed which act as shortcut connections that allow the gradients to flow smoothly into the network during training. The aim is to alleviate the vanishing gradient problem by learning residual mappings and focusing on the differences between the input and the desired outputs rather than directly learning it. Each block contains two paths namely identity path and the residual path which applies additional transformations to the input.
- This model uses the same activation functions as the traditional CNNs to introduce the non-linearity. Thereby classifying the pooling layers, ResNet50 down sample the feature maps, reducing their spatial dimensions to preserve spatial maps.
- Finally, fully connected layers are formed in the end along with the global average pooling layer which typically ends the process of summarising the learned features across spatial dimensions.
- The output layer suggests the final predictions of the network like a traditional CNN algorithm. However, the key difference is that the ResNet50 network introduces residual blocks which allow training without suffering from performance degradation. Further, shortcut connections in this model enables gradients to flow more directly during training and obtain better convergence during the training.
- This gives ResNet50 an edge over the traditional CNNs and results in an improved performance of the network particularly on deep learning networks.

In summary, ResNet50 builds upon the architecture of traditional CNNs by introducing residual blocks and shortcut connections, which enable the training of much deeper networks with improved performance and convergence properties. These innovations make ResNet50 particularly well-suited for tasks requiring very deep architectures, such as image classification and object detection.

Data Analysis and Interpretations

Objective 1: Multi label classification

To address objective 1, a multilabel classification problem, we first addressed the issue of unclear train images by implementing the Dark Channel algorithm for dehazing. This algorithm follows a series of steps:

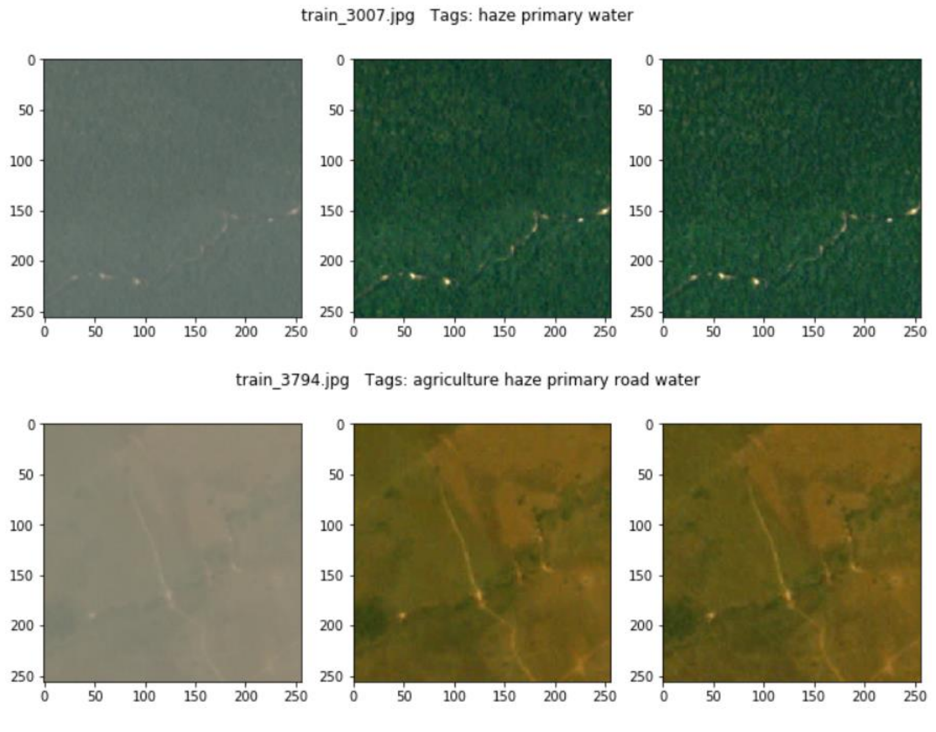
1. Identifying Dark Areas: The algorithm identifies the darkest regions in the image, which typically indicate the presence of haze or fog.

2. Finding the Global Light: It then determines the amount of light coming from the sky or other sources, known as the atmospheric light, by recognizing the brightest areas in the image.

3. Calculating Haze Density: Using the information gathered about the darkest and brightest regions, the algorithm calculates the density of haze across different parts of the image. This involves comparing pixel values to estimate haze strength.[20]

4. Haze Removal: With haze density and atmospheric light determined, the algorithm proceeds to remove haze from the image. It achieves this by adjusting the brightness of each pixel based on the estimated haze density and atmospheric light, resulting in clearer image details and improved visibility.

By employing the Dark Channel algorithm, we effectively enhanced the clarity of train images, facilitating more accurate analysis and classification for our multilabel deforestation detection problem.

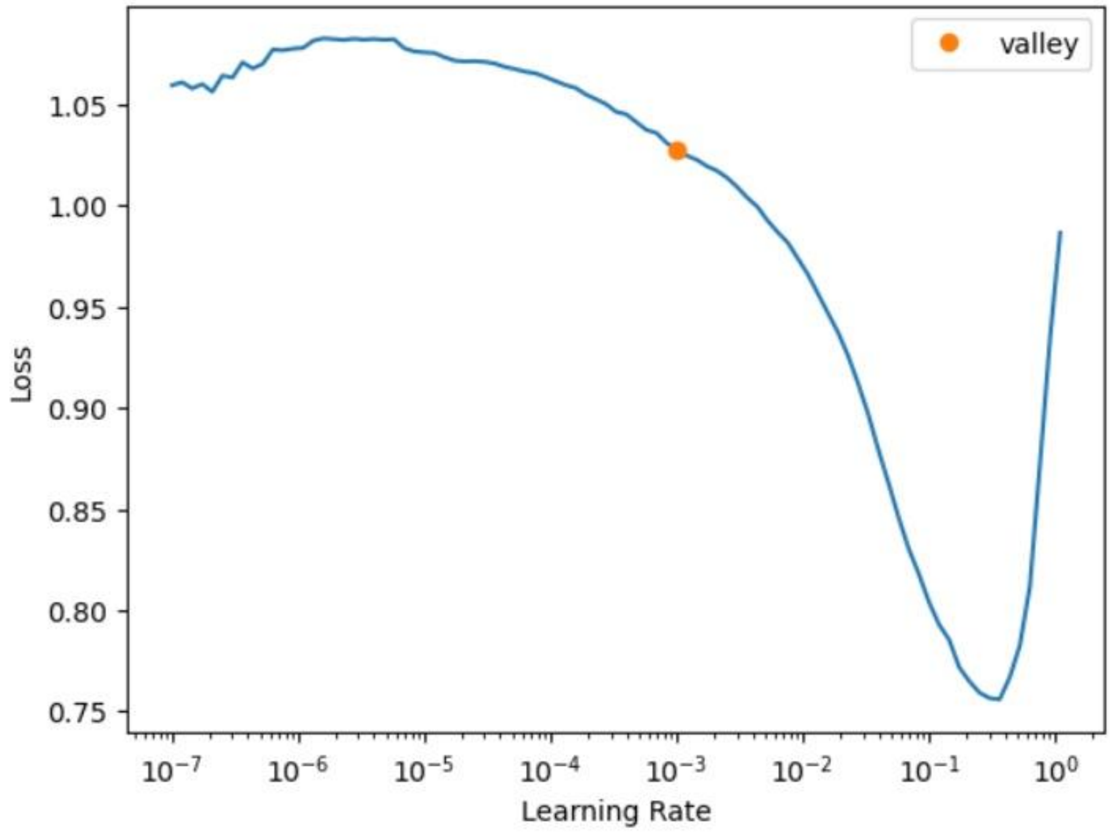


Interpretation: The sample of three dehazed images showcases a remarkable transformation in clarity and visibility over two phases. In the initial phase, the images appear obscured by a dense layer of haze, with details and features obscured and colours muted. However, as the dehazing algorithm is applied, a notable improvement is observed in the second phase. [The haze is effectively removed, revealing sharp outlines, vibrant colours, and enhanced contrast. This transformation not only enhances the aesthetic appeal of the images but also significantly improves their utility for analysis and interpretation.] [21]. The dehazed images now offer clearer insights into the underlying features and characteristics, enabling more accurate interpretation and analysis for various applications such as environmental monitoring or object detection.

After applying the Dark Channel algorithm to dehaze the images, we proceeded to our objective of providing multilabel classifications to the images. To achieve this, we employed the ResNet50 model, a convolutional neural network renowned for its effectiveness in image classification tasks. Using the Fastai library, we initialised the ResNet50 model and trained it on our dataset, which consisted of images labelled with tags related to deforestation and pollution.[12]

Introduced Cyclical Learning Rates (CLR) for neural network training, a lesser-known technique that enhances classification accuracy while reducing the need for extensive iterations.

Instead of a fixed learning rate, CLR enables cyclic variation between reasonable boundary values, optimizing the training process efficiently.



During training, we utilised metrics such as accuracy_multi and FBetaMulti to evaluate the performance of the model on our multilabel classification task. By fine-tuning the model's weights over multiple epochs, we aimed to optimise its ability to accurately predict the presence of deforestation and pollution in the images.[11]

Following model training, we applied the trained weights to our test dataset to assess the model's performance on unseen data. By making predictions on the test images, we were able to evaluate the effectiveness of our ResNet50-based model in accurately identifying instances of deforestation and pollution.

epoch	train_loss	valid_loss	accuracy_thresh	fbeta	time
0	0.776535	0.501960	0.784206	0.414489	59:50
1	0.322740	0.143529	0.954529	0.741460	42:00
2	0.171438	0.119115	0.957059	0.814214	41:21

Interpretation: The reported training loss (0.1714) and validation loss (0.119) indicate how well the model is performing on the training and validation datasets, respectively. Lower values are generally better, as they indicate lower error rates.

- The accuracy_thresh value (0.957) represents the accuracy of the model using a specified threshold for classification. In this case, an image is considered correctly classified if the predicted probability for each label exceeds the threshold (0.2). Higher values are desirable, indicating better accuracy.
- The fbeta value (0.82) represents the F-beta score of the model, which balances precision and recall. A value closer to 1 indicates better performance

Test Predictions:

clear primary

partly_cloudly primary

agriculture clear cultivation primary

partly_cloudly primary

bare_ground;clear;primary

Objective 2: Deforestation and Pollution Prediction

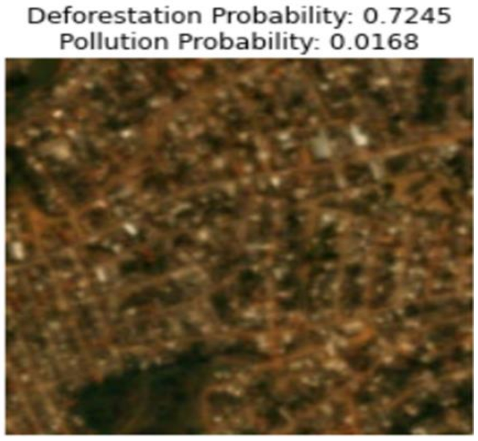
In our project, we leveraged the ResNet50 model for its powerful capabilities in image classification tasks. Initially, we formatted the dataset by creating labels for 'deforestation' and 'pollution' based on associated tags in the image metadata.[19] Then, we split the dataset into training and validation sets, and pre-processed the images by rescaling their pixel values.

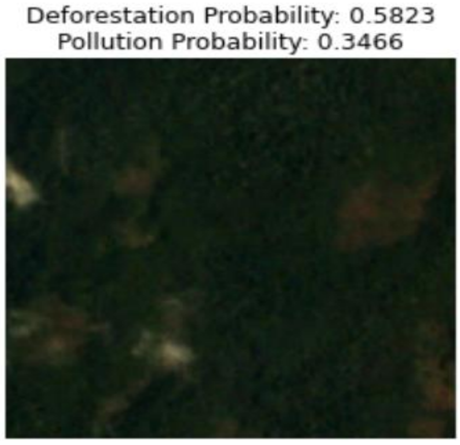
We constructed a deep learning model architecture on top of the ResNet50 base model. This involved adding additional layers such as global average pooling and 3 dense layers, with the last layer having just 2 neurons (Deforestation, Pollution) to facilitate learning more complex patterns from the image features extracted by ResNet50.

For model training, we compiled the model using the Adam optimizer and binary cross-entropy loss function, with evaluation based on the AUC metric. The model was trained for a specified number of epochs using the training data generator, with validation data used for evaluating model performance during training.[13]

Following model training, we developed prediction functions to make predictions on new images using the trained model. These functions preprocess the input image and provide predictions for the likelihood of deforestation and pollution.

Finally, we evaluated the model on a set of test images by randomly selecting five images from the test dataset directory. For each test image, we utilised the trained model to make predictions and displayed the image alongside the predicted probabilities of deforestation and pollution. This comprehensive approach demonstrated the effectiveness of using ResNet50 for our deforestation detection and monitoring task.[14]





Interpretation: As we can see from the above images, the pollution probabilities are low in each case. This is because the deforestation has taken place due to natural causes such as artisanal mining, conventional mining, slash and burn and haze. The deforestation probabilities on the other hand vary from picture to picture or class to class based on whether the land in the image is agricultural, bare ground or a settlement.[15] Therefore, we can say that the model has been trained rigorously and depicts the images to identify rates of deforestation and pollution. Places with high levels (over 65%) of deforestation must be monitored closely to avoid any further clearcutting. The accuracy of this model is 95% after using 3 epochs[22].

Objective 3: Impact of deforestation on Carbon footprint

The Amazon Rainforest, covers approximately 6.7 million sq km area, faces threat from deforestation and is evidenced by increasing deforested area in recent years.

Year	Deforested Area
2020-2021	1.34 million sq km
2021-2022	1.51 million sq km
2022-2023	1.86 million sq km

- In the year 2020-2021, approximately 20% of the total Amazon Rainforest area was deforested, alerting a huge loss of biodiversity and critical habitats.
- While an increase in the rate was noticed in the year 2021-2022 which stood close to 22%
- It peaked at 28% in the year 2022-2023, alerting us to take constant efforts to combat deforestation.[20]

These figures signify the assault of the Amazon Forest. With every increase in % of deforestation there is a loss of habitat due to human activities like agriculture, cultivation, infrastructure development. These activities not only threaten the species endemic to the region but also affect global climate change by releasing huge amounts of carbon stored in this forest area.

Year	Total no. of trees in the region	No. of trees cut (per day)	Carbon footprint (per day)	Oxygen Production (per day)
2020-2021	398 billion	5636 trees	140900 kg	8545 kg
2021-2022	397 billion	2780 trees	69500 kg	4170 kg
2022-2023	395.88 billion	3268 trees	81700 kg	4902 kg

Analysing the total number of trees in Amazon Forest annually gives valuable insights into the rate of deforestation and its impact.
In the year 2021-2022, the total number of trees present were 3.98 billion which was reduced by cutting 5636 trees per day. The total count stood at 3.97 billion in the following year, but the daily count reduced due to the efforts taken to reduce the forest loss. But it accelerated in the recent year with a count of 3268 trees per day. Currently only 395.88 billion trees are present and are expected to further decrease due to increase in land use practices like infrastructure development.[18]

Trees play a vital role in absorbing carbon dioxide, and on an average, it absorbs 25kg per day. The total CO2 absorbed annually is decreasing due to an increase in deforestation. We can observe from the data that with an increase in the cutting of trees every year, an increased level of CO2 gets released. In the year 2021-2022, it increased the carbon footprint by 21.3% and further increased to 81700kg in the year 2022-2023. With every tree getting cut every day there is an increase in carbon print by 25kg.[17]

This also leads to decrease in oxygen production, which is essential to humans and animals. On an average cutting a tree reduces the production by 1.5kg which is enough for two people per day. In conclusion, cutting down a tree every day leads to an increase in carbon dioxide, with a decrease in Oxygen.

Conclusion:

- Dehazing represents remarkable outputs and improves the utility of the overall network in detecting deforestation and the training set.
- With an accuracy of 95%, the ResNet50 trained CNN model predicts accurate probabilities which facilitate the understanding related to deforestation directly using satellite data.
- Obtaining low pollution rates indicate that the major causes of deforestation are natural apart from mining.
- In the last three years, millions of square kilometres of the forest areas have been curbed by deforestation as detected by the algorithm. This evidently indicates the need for implementation of measures associated with afforestation.
- The carbon footprint has surged by approximately 25% each year which can lead to hazardous consequences for the natural habitat and the wildlife in those regions.

Limitations:

- Despite dehazing, the cloud cover in the satellite images obscures land cover features which leads to errors.
- The convolutional networks are trained deeply on this dataset and it might be difficult to generalise it for other datasets from different geographical locations having diverse landforms.
- Identification using distinction in human and natural activities may lead to misclassification. Deforestation occurring due to natural disturbances like forest fires is difficult to diagnose.
- The model can be framed in such a way that it could directly give suggestions for combating deforestation based on the classifier.
- Lack of generalisation and stability limits the application of this project for diverse datasets without training and limits accessibility.

Future Scope:

- A fine-tuning sensor can be applied to enable the model to cater to specific regions or sensor types. This will facilitate generalisation of the algorithm without always having to train the data before detection.
- Techniques like quantifying uncertainty in the deforestation probability maps could be explored.
- A further exploration of methods to distinguish between deforestation caused by human activities and natural disturbances can be delved into, potentially by incorporating additional data sources or developing specialised algorithms by using diverse datasets.
- Time series is a predictive modelling technique that studies the data in a sequential manner.[16] Thus, combining it to our model will lead to a more comprehensive algorithm to provide valuable insights for environmental monitoring.
- Implementing Explainable AI or XAI can be crucial for building trust in the model's outputs and informing conservation strategies. For powerful CNN networks, this technique overcomes the problem of an opaque decision-making process.

Suggestions:

- Preventive strategies can be used if the deforestation rate is low by implementing law enforcements related to lumberjacking, harvesting, mining and illegal land grabbing and so on. These are indigenous territories that must be protected.
- Restorative strategies for afforestation can be used to prioritize restoration of healthy ecosystem and protecting the native species. This will lead to enhancement of oxygen levels and control of the carbon footprint gradually in the long run.
- For critical regions with high deforestation rates, integrated strategies combining both, the preventive and restorative measures must be adapted for a quick as well as long term approach.
- Another way is to spread awareness among the people and adapting to sustainable products in order to reduce agricultural pressure on land.
- By implementing strategies after carefully assessing the root causes such as poverty, population surge, demand for woods or natural causes like forest fires; deforestation can be vanquished.

References:

1. Li, Jinjiang, Guihui Li, and Hui Fan. “Image dehazing using residual-based deep CNN.” *IEEE Access* 6 (2018): 26831-26842.

2. Ortega, M. X., Bermudez, J. D., Happ, P. N., Gomes, A., & Feitosa, R. Q. (2019). Evaluation of deep learning techniques for deforestation detection in the amazon forest. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *4*, 121-128.

3. De Bem, Pablo Pozzobon, Osmar Abílio de Carvalho Junior, Renato Fontes Guimarães, and Roberto Arnaldo Trancoso Gomes. “Change detection of deforestation in the Brazilian Amazon using landsat data and convolutional neural networks.” *Remote Sensing* 12, no. 6 (2020): 901.

4. D'Almeida, Cassiano, Charles J. Vörösmarty, George C. Hurtt, José A. Marengo, S. Lawrence Dingman, and Barry D. Keim. “The effects of deforestation on the hydrological cycle in Amazonia: a review on scale and resolution.” *International Journal of Climatology: A Journal of the Royal Meteorological Society* 27, no. 5 (2007): 633-647.

5. De Bem, Pablo Pozzobon, Osmar Abílio de Carvalho Junior, Renato Fontes Guimarães, and Roberto Arnaldo Trancoso Gomes. “Change detection of deforestation in the Brazilian Amazon using landsat data and convolutional neural networks.” *Remote Sensing* 12, no. 6 (2020): 901.

6. Alzubaidi, Laith, Jinglan Zhang, Amjad J. Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, José Santamaría, Mohammed A. Fadhel, Muthana Al-Amidie, and Laith Farhan. “Review of deep learning: concepts, CNN architectures, challenges, applications, future directions.” *Journal of big Data* 8 (2021): 1-74

7. Guild, Liane S., Warren B. Cohen, and J. Boone Kauffman. “Detection of deforestation and land conversion in Rondonia, Brazil using change detection techniques.” *International Journal of Remote Sensing* 25, no. 4 (2004): 731-750.

8. Perbet, Pauline, Michelle Fortin, Anouk Ville, and Martin Béland. “Near real-time deforestation detection in Malaysia and Indonesia using change vector analysis with three sensors.” *International Journal of Remote Sensing* 40, no. 19 (2019): 7439-7458.

9. Ortega Adarme, Mabel, Juan Doblas Prieto, Raul Queiroz Feitosa, and Cláudio Aparecido De Almeida. “Improving deforestation detection on tropical rainforests using sentinel-1 data and convolutional neural networks.” *Remote Sensing* 14, no. 14 (2022): 3290.

10. Pratiwi, Nor Kumalasari Caecar, Yunendah Nur Fu'adah, and Edwar Edwar. “Early detection of deforestation through satellite land geospatial images based on CNN architecture.” *Jurnal Infotel* 13, no. 2 (2021): 54-62.

11. Adarme, Mabel Ortega, Raul Queiroz Feitosa, Patrick Nigri Happ, Claudio Aparecido De Almeida, and Alessandra Rodrigues Gomes. “Evaluation of Deep Learning Techniques for Deforestation Detection in the Brazilian Amazon and Cerrado Biomes From Remote Sensing Imagery.” *Remote. Sens.* 12, no. 6 (2020): 910.

12. Chua, Leon O. *CNN: A paradigm for complexity*. Vol. 31. World Scientific, 1998.

13. Roska, Tamas, and Leon O. Chua. “The CNN universal machine: an analogic array computer.” *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing* 40, no. 3 (1993): 163-173.

14. Sharif Razavian, Ali, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. “CNN features off-the-shelf: an astounding baseline for recognition.” In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pp. 806-813. 2014.

15. Shivadekar, Samit, Bhavesh Kataria, Sheela Hundekari, Kirti Wanjale, Vijaya P. Balpande, and Renuka Suryawanshi. “Deep Learning Based Image Classification of Lungs Radiography for Detecting COVID-19 using a Deep CNN and ResNet 50.” *International Journal of Intelligent Systems and Applications in Engineering* 11, no. 1s (2023): 241-250.

16. Hossain, Md Belal, SM Hasan Sazzad Iqbal, Md Monirul Islam, Md Nasim Akhtar, and Iqbal H. Sarker. “Transfer learning with fine-tuned deep CNN ResNet50 model for classifying COVID-19 from chest X-ray images.” *Informatics in Medicine Unlocked* 30 (2022): 100916.

17. Mascarenhas, Sheldon, and Mukul Agarwal. “A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification.” In *2021 International conference on disruptive technologies for multi-disciplinary research and applications (CENTCON)*, vol. 1, pp. 96-99. IEEE, 2021.

18. John, David, and Ce Zhang. “An attention-based U-Net for detecting deforestation within satellite sensor imagery.” *International Journal of Applied Earth Observation and Geoinformation* 107 (2022): 102685.

19. Kaselimi, Maria, Athanasios Voulodimos, Ioannis Daskalopoulos, Nikolaos Doulamis, and Anastasios Doulamis. “A vision transformer model for convolution-free multilabel classification of satellite imagery in deforestation monitoring.” *IEEE Transactions on Neural Networks and Learning Systems* (2022).

20. Wang, Jin-Bao, Ning He, Lu-Lu Zhang, and Ke Lu. “Single image dehazing with a physical model and dark channel prior.” *Neurocomputing* 149 (2015): 718-728.

21. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.