Machine learning and plant species identification

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Abstract:

Plants are the backbone of maintaining the earth's ecosystem's balance. All living things in the world primarily obtain oxygen from plants, which also play a critical role in slowing global warming. Affluent Information on plant species and ecosystems is required for the sustainable management and conservation of nature. Though advanced remote sensing technologies have opened the path to high-resolution images for plant species, most of the past research was focused on site/landscape-specific applications. Also, Processing the Remote Sensing data with traditional approaches is time-consuming and requires extensive human supervision. The need to process advanced digital images and achieve precise predictions inspires the adoption of machine-learning techniques in plant research. In this study, we studied research articles that have applied Machine Learning techniques to identify plant species from RS data. Our survey results reveal encouraging trends in recent research' use of CNN and machine learning methods. A number of studies have shown that transfer learning has the ability to improve categorization prediction. Also, the current gaps in machine learning's applicability to detecting plant species are reviewed, and some open questions are provided.

Keywords: Machine learning, remote sensing, deep learning, neural network, image classification, transfer learning

Introduction:

The earth's environment is experiencing widespread problems that demand new solutions. The increased emissions of heat-trapping greenhouse gases have changed average surface temperatures and are expected to continue to rise. The sustained changes in temperature, drought, and snowmelt, resulting in warmer and drier environments, have triggered wildfires in parts of the western United States (Climate Change Indicators: Wildfires | US EPA, n.d.).The United States flora ecosystem is considered one of the richest flora in the world in the context of diversity (“Flora of the United States,” 2022). Sagebrush is an essential component of the United States ecosystem and landscape and is one of the largest continuous ecosystems. The plant provides important habitat for various wildlife, including the famous sage grouse and over 350 other species. The sagebrush landscape in the western United States covers more than 175 million acres of public and private property (Sagebrush Conservation | U.S. Fish & Wildlife Service, n.d.). Sagebrush plays a vital role in the arid western water cycle. Other native plant species in the sagebrush steppe, such as mugwort plants, help keep soil intact when it is restored after resources such as oil, gas, and trona have been extracted(*Celebrating Sagebrush*, 2018; *Sagebrush Conservation | U.S. Fish & Wildlife Service*, n.d.). In addition, the sagebrush country contains environmental, cultural, and economic resources of national significance. These plants feed a variety of wildlife and herds of rangeland animals and thus contribute to the earth’s ecosystem and environment(Celebrating Sagebrush, 2018). Knowledge of plant species’ contribution to ecosystem functions and services is essential to better understand environmental issues.This requires spatially detailed information on plant species composition over vast areas(Fassnacht et al., 2016). Information about plant species has also aided other environmental studies, such as mapping wildlife habitats and estimating the number of insects in forests (Kennedy & Southwood, 1984). Several studies have highlighted the value of plant species maps as stand-alone products for forest management (Vauhkonen et al., 2014). Accurate plant and species information is essential for assessing biodiversity and improving a healthy ecosystem(Lutz et al., 2018).

Several approaches have been used to study and predict plant detection by uniting field-level and remote-sensing data(Fassnacht et al., 2016). Past approaches, like traditional biological identification methods, generally require field data focusing on the physical characteristics of the plants (Chapter 25: Plant Identification, n.d.). Statistical approaches like maximum likelihood classifier and clustering were used widely decades ago, but one of the pre-requisites of using them was that the data needed to follow specific distribution e.g, normal distribution (Fassnacht et al., 2016). Another powerful technique is Object-based image analysis (OBIA), which is extensively used in remote sensing image analysis and plant identification(Guirado et al., 2017). When defining objects in an image, OBIA considers each pixel's spatial, spectral, geometrical, and contextual attributes and how they relate to each other to locate the pixels into groups(*OBIA - Object-Based Image Analysis (GEOBIA) - GIS Geography*, n.d.). The main idea is to identify meaningful objects from images, e.g., individual trees, bare soil, wetland, roads, buildings, etc. Nevertheless, the method has some drawbacks. OBIA in the classification settings for one specific image can only be applied to that image; the settings can't be transferred to a different image and thus require heavy human supervision(Guirado et al., 2017). All these methods require experts' valuable time and extensive effort. Though the traditional approaches had reasonable performance, they were time-consuming, costly, and arduous; these limitations drove the need for new strategies for classifying plant species to improve environmental projects. For this reason, recent researchers have been using Machine Learning (ML) and Deep Learning(DL) tools as an alternative to past techniques to precisely classify plant species(Fassnacht et al., 2016;Borowiec et al., 2021). Machine Learning approaches have been applied to many parts of the earth’s landscapes for classification. They have proven helpful for regression and classification tasks and supervised and unsupervised tasks(Bojamma & Shastry, 2021).

Machine Learning techniques commonly found in the literature for plant identification studies include logistic regression, decision tree, support vector machine, random forest, and artificial neural network(Arshed et al., 2022; Fassnacht et al., 2016). For example, authors of (Guirado et al., 2017; Marconi et al., 2022) have used artificial neural networks to identify plants from remote sensing data. Artificial neural networks(ANN), however, have also been combined with classical ML algorithms in several studies. Recent efforts in species classification use either deep learning methods or an ensemble of machine learning, showing promising improvements over more traditional approaches such as random forest, support vector machines, or multi-layer perceptron classifiers. Furthermore, as machine learning technology advances, sophisticated models like Deep Residual Network (ResNet), VGG-16 & VGG-19 have been proposed for automatic plant identification(Fassnacht et al., 2016; Guirado et al., 2017; Sun et al., 2017).In addition, the recent use of transfer learning combined with the CNN model has shown better performance in achieving accuracy (Borowiec et al., 2021; Marconi et al., 2022).

We found that Data Science and Artificial intelligence are powerful tools to help researchers evaluate environmental data and find underlying issues and solutions that benefit humanity and the environment. Moreover, data science can be crucial in achieving the UN’s sustainable development goals(Nandi, 2022). This study aims to survey and review previous articles that have applied machine learning and deep learning to classify sagebrush plant species.We reviewed research papers that applied machine learning to identify plants to achieve our goal.

To that end, we surveyed research publications from Google Scholar for corresponding research works and identified 5 seed papers. Details of the seed papers are presented in Table1.

Table 1: An overview of common ML tools used in ecological studies.

Name	Journal	ML and deep learning algorithms
Continental-scale hyperspectral tree species classification in the United States National Ecological Observatory Network	Remote Sensing of Environment	KNN,RF,Gradient Boasting,SVM
Deep-learning Versus OBIA for Scattered Shrub Detection with Google Earth Imagery: Ziziphus lotus as Case Study	Remote sensing	ResNet,GoogLenet, OBIA
Review of studies on tree species classification from remotely sensed data	Remote Sensing of Environment	SVM,KNN,RF
A Light Weight Deep Learning Model for Real World Plant Identification	Institute of Electrical and Electronics Engineers (IEEE)	Resnet-50
Satellite and Scene Image Classification Based on Transfer Learning and Fine Tuning of ResNet50	Mathematical Problems in Engineering	ResNet

2. An overview of Remote sensing and ML techniques:

This modern world's data is primarily unstructured, which means this data can't be organized in rows and columns, for example, image, audio, or video. The current era can be called an era of data where remote sensing imagery is playing a crucial role. The major advantage of RS (remote sensing) is collecting information about any object on the ground without physical contact with it. For the last decade, ML has been at the heart of modeling for digital image classification(Fassnacht et al., 2016)(Bojamma & Shastry, 2021). With the increase of RS imagery data, the application of ML is increasing in parallel. This section will present an overview of Remote sensing and the basic idea of ML techniques.

2.1 The universal significance of Remote Sensing:

Data from remote sensing can speed up operations and decision-making in the public and private sectors and also allows monitoring of revegetation rates across an arbitrary landscape (*REMOTE SENSING DATA: APPLICATIONS AND BENEFITS*, n.d.; *NOAA's National Ocean Service*, n.d.). The huge amount of new data from remote sensing, which is complex, necessitates scalable classification methods. It is challenging for traditional approaches to extract insights from remote sensing imagery. Machine learning applications and advancements in remote sensing imaging provide the door to developing plant species categorization algorithms at the level of individual tree crowns(- *REMOTE SENSING DATA: APPLICATIONS AND BENEFITS*, n.d.).

Authors of the seed papers mentioned that ML offers powerful techniques like image classification, feature extraction, and Deep Learning. Our study shows that ML and DL can potentially classify images, especially in the case of plant species detection(Guirado et al., 2017; Marconi et al., 2022). The application of ML in the field of biology and image recognition has been practiced for years. Authors (Borowiec et al., 2021) presented statistics from their 818 supplementary study collection that 496 studies used deep learning, a broader ML family. In addition, the primary goal of those studies was image classification. Next section we will discuss basic ideas of ML techniques.

2.2 Basic ideas of Machine Learning and deep learning:

According to computer pioneer Arthur Samuel, "Machine Learning relates with the study, design, and development of the algorithms that give computers the capability to learn without being explicitly programmed." ML uses algorithms that are programmed in such a way that allows systems to learn and make informed decisions based on experience without being specifically programmed. ML algorithms perform intelligently and have the potential to overcome the setback of traditional approaches. Typically, machine learning tasks are divided into four major categories discussed in Table 2 mentioned below (Sarker, 2021, n.d.; Sengupta,2020).

Table 2: Four major categories of ML

Learning Types	Description	Process
Supervised learning	The computer is presented with labeled training data and training examples. The goal is to correctly map an input to an output that it had not previously seen during training.	Regression, Classification
Unsupervised learning	A data-driven process where the learning algorithm goes through a set of unlabeled data and tries to produce meaningful results.	Clustering, feature learning, dimensionality reduction, identifying patterns
Semi-supervise d	Operates on labeled and unlabeled data. It can be said that this is a fusion of both supervised and unsupervised approaches	Classification, Clustering
Reinforcement learning	This algorithm enables machines to automatically evaluate the optimal behavior based on reward or penalty from experience. The program aims to accomplish a specific task while interacting with a dynamic environment.	Classification, control

Note: Adapted from (*Https://Www.Guru99.Com/Machine-Learning-Tutorial.Html*, n.d.; Johnson, 2020; Saha, 2022; Sarker, 2021)

The primary two traits of supervised ML are classification analysis and regression analysis. This paper explores the classification field in the shade of remote sensing data.

In general, classification involves ordering objects into groups or classes based on their similarity and ordering them into classes in a meaningful way(Do we Need a Real Taxonomy of eBusiness Models—CiteSeerX - MOAM.INFO. (n.d.). Generally, classifying data into classes or groups is done through two significant steps in the ML process. The first step is the training phase, where the algorithm is trained with labeled data to build a model, find any pattern or shape in the data, and create knowledge about the data. The second step is called the testing step, where the trained model from the first step is applied to a set of unlabeled data; the model uses learning from the previous step and predicts the class label for the unlabeled data(Johnson, 2020). The model works as a function of the values of other data attributes, that try to predict a class for each unlabeled data. This phase is also called predictive modeling. Below Figure 1 illustrates the general layout of a predictive model based in the field of machine learning.

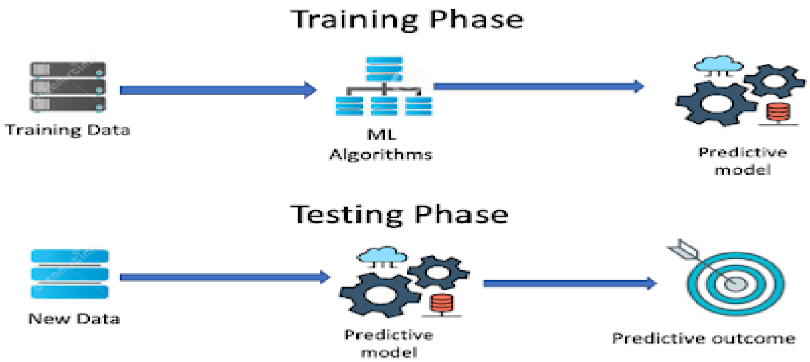
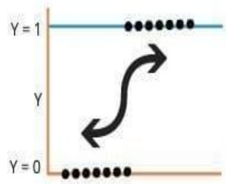
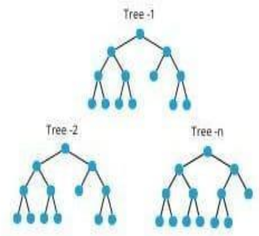
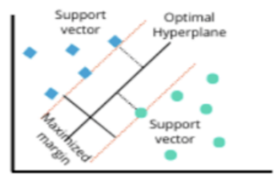
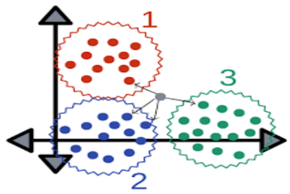
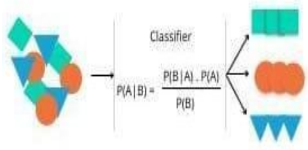


Figure 1

Table 3 explains the basic idea of frequently applied ML algorithms mentioned in the reviewed studies.

Algorithm name and invention date	Description	Image
Logistic Regression Pierre Francois Verhulst(1838)	This probabilistic statistical model depends on its explanatory variable for the outcome of explained or target variable. It's another version of linear regression applied to a categorical dataset. It is the most popular and commonly used classifier algorithm.	

Random Forest (RF) Leo Breiman in 2001	This algorithm formulates several questions regarding the characteristics of the explanatory variables, and the potential responses are arranged in a hierarchical framework. (Guirado et al., 2017)	
SVM(Support Vector Machine) Vapnik and Chervonenkis (1971)	It creates dimensions accordingly to the features in the dataset and plots each data item as a point. Then, it performs classification by finding the hyper-plane that differentiates the classes (Motlhabi et al.,2021)	
KNN(K Nearest Neighbour) Evelyn Fix and Joseph Hodges (1951)	In this algorithm, an object is classified based on the class attributes of its K nearest neighbors.	
Naive Bayes (NB) Thomas Bayes	It is based on the Bayes theorem and assumes that the predictors in the dataset are independent of each other. This algorithm calculates the posterior probability for each class using a Bayesian equation. The prediction's output is the class with the highest posterior probability.	

Note: datasciencedojo, Johnson, 2020; Saha, 2022; Sarker, 2021

2.3 Fundamental of Deep Learning:

Deep Learning and Machine Learning belong to the family of artificial intelligence but are different. The architecture of DL algorithms is inspired by how the human brain functions(AI, 2020). In the human brain, the brain neurons are the functional units interconnected with each other in a layered structure but in deep learning; a neural network plays the same role as the brain neuron. Therefore, it is called deep learning because it combines multiple layers, e.g., input, hidden, and output; with each layer, the whole process becomes deeper(Sarkar, 2018). These layers are interconnected and create an Artificial

Neural Network(ANN), which learns from the input data and makes intelligent decisions without human support for the future (Gunen, 2021).

This multi-layered ANN functions similarly to a biological neural network of the human brain and can process complex data(Borowiec et al., 2021). Deep learning algorithms need little human intervention because of the automatic feature engineering. In comparison, Machine Learning algorithms have a simple structure and only partially earn all functions, especially when the input and output models have a complex relationship. In addition, these ML techniques need expert intervention for feature engineering(Sarker, 2021; Shabbir et al., 2021).

2.3.1 Neural Networks (NN):

A NN is a fundamental deep learning unit. Neural networks often aim to detect edges in the first layer, followed by shape detection in the middle, and task-specific features in the latter layers. Each node or neuron is connected to another and has a threshold and weight that go along with it. Any node whose output exceeds the defined threshold value is activated and provides data to the network's uppermost layer (Johnson, 2020; Sarker, 2021). Otherwise, no data is transmitted to the network's next layer. A node comprises two main parts: the summation and the activation function (Shi, 2022). A neuron takes input data (x_1, x_2, x_3,…x_i) as input, here neuron numbers are determined and the same as the input data dimension. In Figure 2, x_i is the i-th input feature and i-is the dimension of the data. Multiple neurons, each with a specific weight (w_1, w_2, w_3,….), and then passes the result to a function called the activation function to produce an output which could be defined as a function the inputs like f(x)=y.

Every ANN has a set of weights and biases associated with each neuron, and a set of non-linear activation functions that are applied to the weighted input. In Figure 2, g is the activation function, some of the vastly used activation functions are relu, sigmoid, tanh. In figure 2 w_i is the weight, bias b_i is the bias of the neuron associated with the i-th input feature. z_i is an intermediary function that is based on weight. Basically, this function is a linear combination of the input x with its coefficients w, plus a bias b (Borowiec et al., 2021; Johnson, 2020; Sarker, 2021; Shi, 2022).

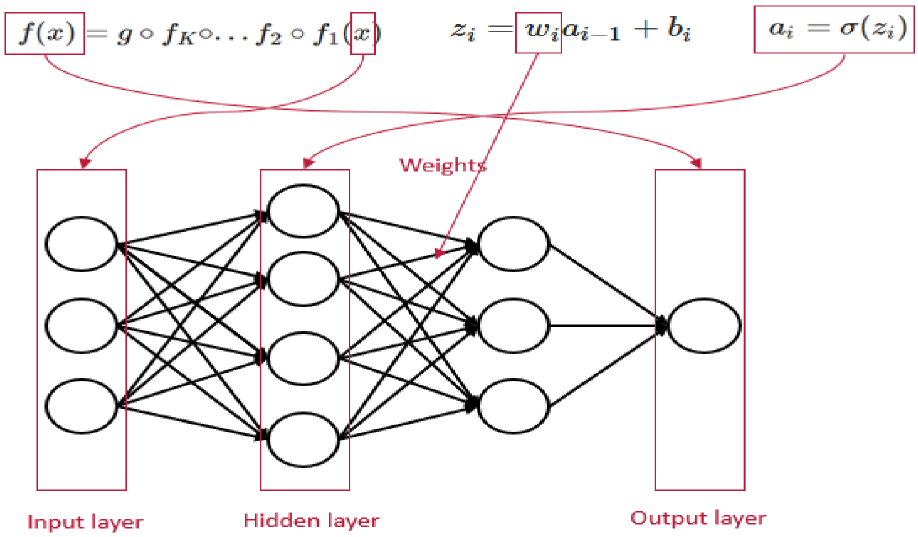


Figure 2 (Shi, 2022)

Some popular and frequently used DL algorithms are Multi-layer Perceptron (MLP), Convolutional Neural Networks (CNN, or ConvNet), Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN) (Sarker, 2021). In the following, we discussed CNN, which is vastly used for image classification analysis.

2.3.2 Convolutional Neural Network (CNN, or Conv Net):

Convolutional Neural Networks (conv net) are special multi-layer neural networks where neurons connect the outputs and inputs with weights. The key difference between ordinary NN and ConvNet is that ConvNethave neurons are arranged in 3D volume (width, height, depth) with some differentiable function that may or may not have parameters(*CS231n Convolutional Neural Networks for Visual Recognition*, n.d.). These are one of the deep learning networks and are initially designed for image processing (Valueva et al., 2020).

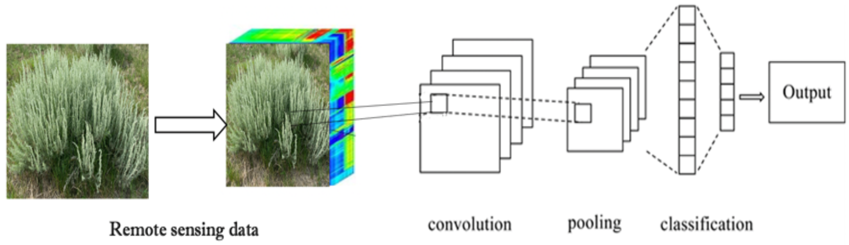


Figure 3

Generally, in CNN input layers hold the pixel values of the image, most of the time images are arranged in three dimensions which is width, height, and depth. Generally, the depth refers to three color channels Red(R), Green(G), and Blue(B). In Figure 3, input layer contains a remote sensing image with three color band channels (R, G, B) (*CS231n Convolutional Neural Networks for Visual Recognition*, n.d.). In this paper, we describe two crucial building blocks of CNN classification that is convulation layer and the pooling layer.

The convulation layer (conv layer) is the backbone of CNN which does a significant percentage of computational tasks. This layer does the computation between input and output neurons with their weights, resulting in a three-dimensional volume with a determined number of filters. These filters are made up of a small matrix of weights(Brownlee, 2019). Each convolution takes the dot product of the input value and filter value, filters are applied to the entire input image in a sliding way to extract features (Figure 4). This is done to create feature maps summarizing the existence of such features in the input image(Borowiec et al., 2021). The early conv layers capture low-level features such as horizontal or vertical lines, dimensions, colors, and angles, while the deeper layers capture comparatively more complex features like objects and shapes(Saha, 2022). All the layers play a critical role in making a reliable prediction for classification.

Figure 4 explains the sliding approach of filters to create a feature map

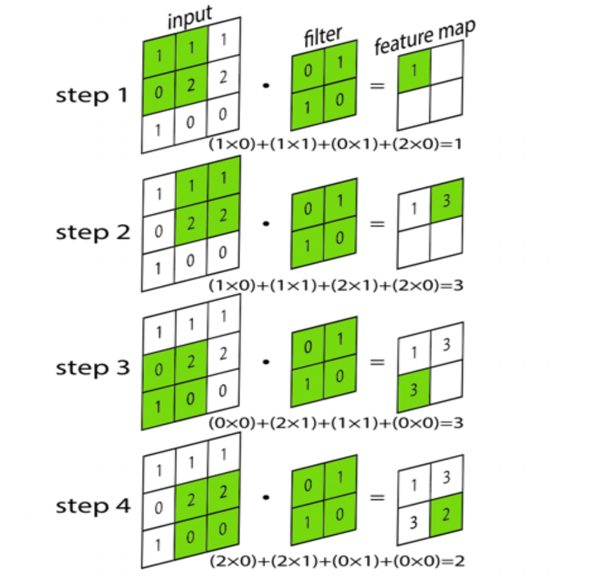


Figure 4 (Borowiec et al., 2021)

Principally, convolutional layers are followed by pooling layers and may be repeated multiple times in a network. As a result of the pooling layer, a new set of pooled feature maps is created from each individual feature map from the conv layer(Brownlee, 2019; *CS231n Convolutional Neural Networks for Visual Recognition*, n.d.). In addition, this layer reduces the spatial dimension in the feature maps and the number of parameters in the network. These layers transform the input image into a shape that allows it to be flattened into a column vector and also reduce non-linearity(Saha, 2022). Generally, the pooling layer is followed by ReLU Layer, which represents the rectified linear unit. In this layer, negative values are replaced with zero with the help of an activation function, thereby increasing nonlinearity. Neurons are then connected to activations of the previous layer(Sachar & Kumar, 2021a). Lastly, the output layer or classification layer, which is often initiated by single or multiple NN, these NN's converts the output of conv layers in an appropriate shape for classification(Saha, 2022; Shi, 2022).

Currently, the most commonly used software implementing CNNs is the python libraries of Tensorflow by GoogleTM and PyTorch by Facebook AI group. These open-source libraries hold several pre-trained models. The frequently used pre-trained model for image classification is listed below.

Year	CNN	Architecture	Developed by
2015	ResNet	architecture consisted of a 152-layer deep CNN	Kaiming He
2014	GoogLenet	architecture consisted of a 22-layer deep CNN	Google
2014	VGGNet	architecture consisted of a 16-layer deep CNN	Simonyan and Zisserman

Table 4

2.3.3 Transfer learning:

Transfer learning is a powerful ML technique that allows for transferring knowledge from one domain to other domains with similar problems. The goal is to go beyond typical ML models' single-task learning strategy by using knowledge gained from one job to solve other tasks that are related to it(Sarkar, 2018). Generally, a NN's gain knowledge as they solve a task; this knowledge is compiled into "weights" for that network. Transfer learning involves extracting these weights and directly applying them to new tasks(Shabbir et al., 2021). Transfer learning generally works by freezing the hidden layers, removing or customizing the last layer, and then retraining the model. Using transferred features in the initialization process reduces the distance between the base task and the target task since the base task does not have to be trained from scratch. Fortunately, many pre-trained architectures such as VGG-16, ResNet, GoogLenet, DenseNet121, and MobileNetV2 are directly available in the Tensorflow, Keras, and PyTorch libraries(Borowiec et al., 2021).

Implementing transfer learning automated plant species identification from images could be immensely useful for land-use planning and biodiversity conservation**.** However, research for plant species identification has always been challenging because collecting new field images requires tremendous effort and cost, especially in the case of labeled data(Borowiec et al., 2021; Sachar & Kumar, 2021b)**.** Images of plants collected from two different places can be analyzed with the same model. With that in mind, it is worth investigating the existing data and pre-trained models for more satisfactory plant identification.

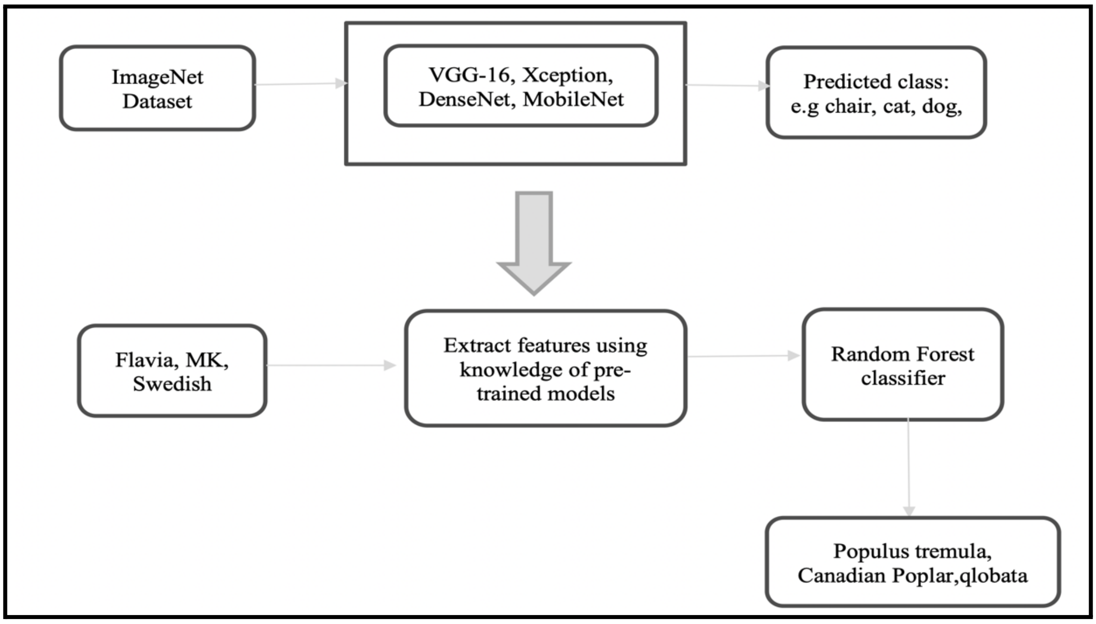


Figure 5 (Sachar & Kumar, 2021b)

Figure 5 shows a proposed system methodology for transfer learning by authors (Sachar & Kumar, 2021b). This is also an ideal example of implementing transfer learning in plant identification. The authors used pre-trained CNN models like VGG-16, Xception, MobileNet V2, and DenseNet 121 and trained onImageNet. ImageNet comprises almost 1.2 million images whose features and weights are transferable between networks. The features (knowledge) learned by the fully connected layers of these models are then fed as input into the selected classifier of the testing phase, which is Random Forest in this case. For testing, the researchers used three publicly available datasets Swedish, Flavia, and MalayaKew. Lastly, the RF classifier predicts a class label for the input data.

3. Application of ML/DL in recent research:

Our review of the current status of studies showed that the adaptation of automated plant identification approaches like ML/DL is getting popular over traditional approaches in recent years(Bojamma & Shastry, 2021). Biologists are willingly adopting the advancement of computerized techniques, especially in the field of image processing ((Fassnacht et al., 2016).

Recent efforts in species classification using either deep learning methods or an ensemble of machine learning show promising improvements over more traditional approaches such as random forest, support vector machines, or multilayer perceptron classifiers(Marconi et al., 2022). The authors of (Marconi et al., 2022) study used the hyperspectral L3 data from the NEON Airborne Observatory Platform (National Ecological Observatory Network). The study shows the development of generalizable species classification models based on data across different forest types. The authors built two sets of models:(1) a general model integrating data from 27 NEON sites and(2) 27 separate models, each using only the data from a single NEON site and covering a region of a few hundred km2(Marconi et al., 2022). The study (Marconi et al., 2022) shows species classification was at pixel level using an ensemble of five classifiers : (1) k-nearest neighbors (KNN) classifier (2) random forest(RF) classifier (3) a fully connected multilayer perceptron, (4) histogram gradient boosting and (5) bagging classifier with support vector machine(SVM). The researchers used F1 and Accuracy as result assessment tools. The results were impressive, classification results for the average individual tree, the general model achieved an accuracy of 77%, which was better than the site-specific models' accuracy of 70%.

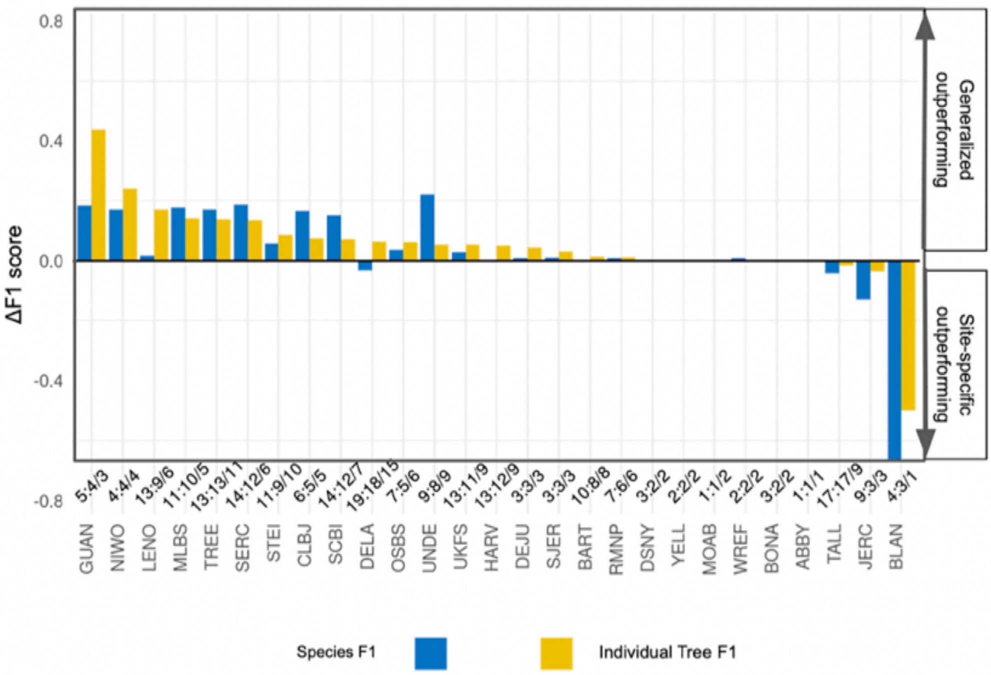


Figure 6 (Marconi et al., 2022)

Figure 6 shows the performance of both generalized and site-specific model classification. The horizontal line represents the sites' names, and the vertical line represents the F1 score value. The upper part of the plot, which is the positive value, shows sites where the generalized model outperforms. The lower part, which belongs to negative values, refers to the sites where the site-specific models outperform. The blue and yellow bars correspondingly refer to species level F1 and individual level F1 scores. And the number above the sites' names refers to the species' frequency in the training phase (general: site-specific model) (Marconi et al., 2022).

In another example, the researchers of (Guirado et al., 2017) used a mixed-methods approach of OBIA and CNN for scattered shrub detection (case study: *Ziziphus lotus*). An in-depth study of this paper showed the existing works using DL, particularly CNN, in the field of RS data are divided into two categories. An image with multi-band (more than three spectral bands) and a high resolution is required to perform classification with CNN by one of the groups. The other group performs the classification of remotely sensed RGB images. Both groups have shown reasonable accuracy. The Authors (Guirado et al., 2017) in this paper analyzed the potential of CNN-based methods (e.g., ResNet-classifier, GoogLeNet) to detect plant species and compared them to the cutting-edge OBIA (Object-Based Image Analysis) method. The experiments demonstrated that the best CNN-detector, the ResNet-based classifier with transfer learning, achieved up to 12% better precision, up to 30% better recall, and a significant balance between precision and recall than the OBIA-based methods (Guirado et al., 2017).

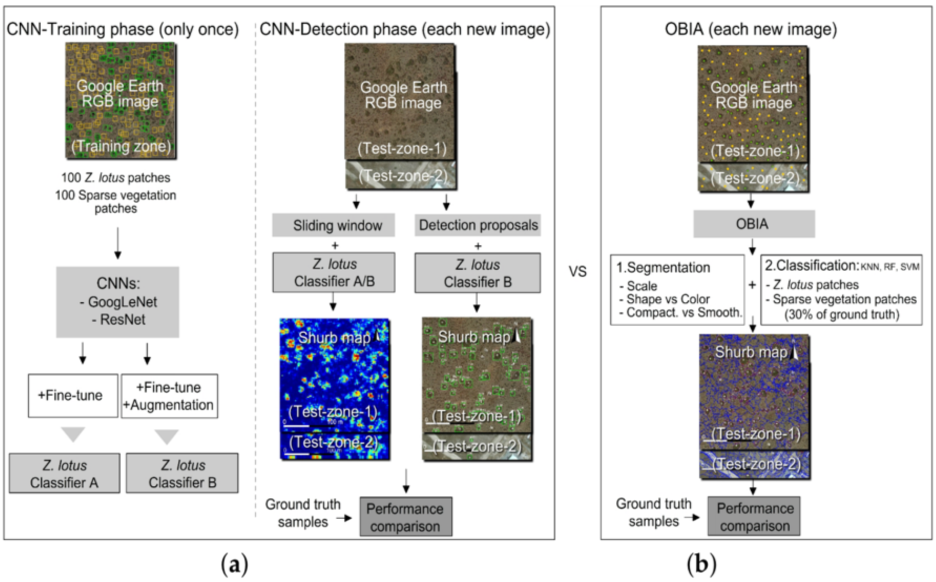


Figure 6 (Guirado et al., 2017)

Figure 6 shows the study results of authors (Guirado et al., 2017) for *Ziziphus lotus* shrub mapping using remote sensing imagery. Part (a) displays both the training and detection phrases. The flow chart shows the training phrase composed of two CNNs: GoogleNet and

ResNet. Following that, two classifiers (classifier A and classifier B) are built after fine-tuning and data augmentation. Two approaches are used in the detection phase: a sliding window and a detection proposal. The final step compares the performance of the classifiers with ground truth samples. In part (B), OBIA for each new image is displayed. It includes two steps: 1. segmentation and 2. classification (KNN, RF, SVM) with 30% ground truth for training. A final comparison was made between ground truth samples and classification results. It is mentioned that a combination of ResNet and detection proposal techniques provided the best performance(Guirado et al., 2017).

4. Gaps in Machine Learning Applications and Future Paths:

In this study, we reviewed several past publications that have used Machine Learning techniques and deep learning for image classification, especially to identify plant species from remote sensing data. While our analysis is limited to the publications reviewed in our study, significant gaps in machine learning applications have been identified:

- *Need for repetition in algorithm and limitation in transfer learning techniques*:

To detect a specific object (e.g., a particular plant species individual) in an input image, the traditional ML algorithm (e.g., by using algorithms such as the k-nearest neighbor, Random forest, or Support vector machines)classifies the processed image data based on their similarities. This procedure has to be repeated and optimized for every single site/landscape. Therefore, the knowledge acquired (i.e., the image segmentation process, feature extraction, and classification settings) from one input image cannot be directly reutilized in another.

- *Shortage of broad-scale general models and integrating information from multiple datasets and locations*:

We noticed that recent works target single regions, so even though they provide valuable surveys for key species across different stand ages and topographic positions, their use still needs to be expanded to relatively small regions. For remote sensing data, a single site training dataset often lacks variation in spectral characteristics that can occur for each species due to intraspecific variation. There need to be more studies comparing broad-scale general models with integrating data from several sites versus site-specific models.

4. Open questions:

While reviewing the publications for this study, we noticed that most of the data sets typically used for the training ML models were site-specific, that is, trained and used for predictions within a limited geographical area. As a result, the model was also site-specific and was not useful for other applications. However, only a few studies consider integrating data from several sites and making a general broad-scale model that shows remarkable outcomes(Marconi et al., 2022). Hence our question is whether using a general broad-scale rather than a site-specific model can improve the ability to predict plant species?

Most studies collected data using remote sensing and machine learning algorithms for classification but did not use machine learning techniques known for image analysis(Fassnacht et al., 2016);(Arshed et al., 2022). Hence we ask our second question: is: would a convolutional neural network produce more accurate predictions relative to traditional ML models for plant species detection principally for image analysis?

Classical machine learning often requires that important data features are first identified using expert domain knowledge; as a result, they tend to need extensive human supervision and are pretty brittle in practice when deployed. (Guyon et al., 2008). Deep neural networks overcome this by automatically discovering the most crucial data features and relevant patterns. So, the third question is : whether using deep learning for species detection could be more efficient in terms of labor, time, and cost?

We observed that most of the prior studies didn't investigate the reasons for the accuracy loss of the implemented model.There could be a number of causes for this accuracy reduction, including modifications made to the data structure, model architecture, or training procedure. We hope that determining which part of the model or data is causing the accuracy loss will improve the performance of machine learning models. Thus, our last question is Why most of the papers didn’t check which part of the data or model is the reason for accuracy loss?

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