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# Eucalyptus Trees Nutrition Deficiency Detection Using Deep Learning Techniques

Mesfin Alemu Mekonnen[1]*, Hailay Beyene[2], Hussein Seid[3]

[1] *Department of Computer Science, Kotebe University of Education, Addis Ababa, Ethiopia*

[2] *Department of Computer Science, Addis Ababa University, Addis Ababa, Ethiopia*

[3] *Department of Software Engineering, Addis Ababa Science Technology University, Addis Ababa Ethiopia*
*Corresponding email*: mesfine.alemu@aastu.edu.et*

Eucalyptus is one of the most widely cultivated tree species in Ethiopia and as a major source of fuel wood and construction material. A few researchers have attempted to do their research in other countries try to solve Eucalyptus tree nutrient deficiency by identifying the leaf part of the tree. According to this idea many nutrition deficiencies that affect Eucalyptus tree vegetation growth in Ethiopia. In this article, a model was developed using the deep-learning techniques, that developing Eucalypts trees nutrition deficiency detection. The study employs four distinct architectures, using one of a cloud software tool that known as "Google colab" or "Google collaborator"; MobileNet, ResNet50, DenseNet, and InceptionV3 to analyze and classify nutrient shortages from Eucalyptus tree leaf images. We collected 843 images, from its dataset 80% of the data are utilized for the training set, or a total of 674 images for all class; the remaining 10% are used to test the model and 10% images are used for the validation set for each class, MobileNet received a more hopeful result scored based on the report of classification parameters between all models. The Eucalyptus nutritional deficiency was correctly identified based on the collected images. A thorough investigation of the above mentioned models during the process of differentiating between the nutrient-deficient and healthy managed the following nutrients' Boron (B), Calcium (Ca), Iron (Fe), Magnesium (Mg), Nitrogen (N), Phosphorus (P), Potassium (K), and Healthy on images of the leaves. Additionally, the model's data performance could be improved. Better forest management will result from this research's difficult way of monitoring Eucalyptus tree health, which will benefit precision agriculture production.

*Keywords*: Eucalyptus, tree nutrition deficiency, Convolutional Neural Network, Deep Learning, Pretrained model

## 1. Introduction

Nowadays, the most planted genus of trees worldwide is Eucalyptus, which comprises over 500 species. Native to Australia, where there are over 600 different species of Eucalyptus [1]. Emperor Menelik II (1868-1907) introduced Eucalyptus (bahir zaf) to Ethiopia in 1895 from different countries, mainly from Australia. Menelik II saw the potential advantages of this native Australian tree that grows

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quickly. Due to its quick growth, adaptability to different climates, and use for shade, lumber, and even medicine, Eucalyptus trees are prized. Menelik saw a chance to improve both agricultural output and urban growth because of Ethiopia's varied geography and climate. Seedlings were raised in a nursery on the grounds of the royal palace in order to make this introduction easier. Before being widely distributed, different plants could be acclimated to the Ethiopian environment in this nursery, which functioned as an essential experimental garden. Following the seedlings' care, Menelik II directed their planting in the capital city of Ethiopia, Addis Ababa, where they would enhance the city's aesthetic appeal and fulfill useful functions like shade and firewood [2][3]. Supplements are necessary for plants to grow and yield. Plant growth and development depend on a proper nutritional balance. Plants cannot complete their vegetative or reproductive cycles in the absence of any fundamental component, and as a result, they will have deficiency symptoms [4][5]. This suggests that in order to support farmers and those making investments in the agriculture sector, technological solutions are required. Additionally, the issue affects emerging nations greatly since agriculture is essential to their economies and means of subsistence; this is particularly true in Ethiopia, where the majority of the population is farmers.

## 2. Related Work

In this study they try to Customizing the nutrient diagnosis of young Eucalyptus trees to factor-specific levels they gathered 1861 observations from 148 sites, 48 different types of soil, and eight clones, trees planted (97%) were between 0.9 and 1.1 years old They using tissue compositions alone, the random forest classification model [6].

This study is to evaluate remote sensing's capacity to quickly identify macronutrient and micronutrient deficiencies in young trees. Full-waveform hyperspectral data (350 nm–2500 nm) from 135 young trees planted in individual pots were gathered in a controlled forestry nursery setting. They tested manganese (Mn), iron (Fe), copper (Cu), zinc (Zn), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), manganese (N), and boron (B) in young, commercially planted forest types. This study used integrated random forest (RF) measures of variable relevance to determine the most important wavebands for identifying nutrient deficits. As they advise experimenting with the usage of targeted electromagnetic spectrum regions, such as portable near-infrared technologies, to lower noise and speed up computation imbalance [7].

An analysis of leaf properties, they develop an artificial neural network model that can identify and categorize tomato nutrient deficiencies. The two main characteristics that are utilized to determine a nutritional shortage in a leaf are its color and shape. The performance of the suggested system is affected by the comparison of several segmentation techniques, such as hue-based and threshold-based systems. The findings demonstrate the excellent accuracy with which the suggested method was able to categorize and identify nutritional deficits [8].

A diagnostic system using digital image processing could find the flaws much sooner than the human eye could. As a result, the farmers would be able to take prompt and suitable corrective action. The primary goal of this research is to examine studies that identify nutritional deficits in plants using image processing techniques [9].

This study makes the assumption that varying Boron (B) levels in Eucalyptus affect the plant's reflectance at various wavelengths [10].

Most plant species depend on nutrients for their growth and development. The role of nutrients in various genotypes in perennial trees is not well understood, yet. Applying three distinct nutrient levels (low, sufficient, and high) to two distinct cultivars of Eucalyptus urophylla (a low-growth cultivar ZQUB15 and a high-growth cultivar ZQUA44) produced various results and levels of expression and growth were examined. Based on their expression patterns, differentially expressed genes (DEGs) are clustered into six subclusters. Their findings show that, in response to abiotic stressors, distinct genotypes may develop distinct routes to coordinate plant survival [11].

## 3. Research Methodology

Research methodologies by answering research questions that includes data collection, data preparation, system hardware and software configuration, model performance evaluation techniques, to determine which models performed the best and identify them for further use, a particular technique was employed to evaluate each model's efficacy and performance.

### 3.1. *Data Preparation*

Collect a large dataset of images of Eucalyptus leaves, including both healthy leaves and leaves showing different types of nutrient deficiencies; where healthy leaves appearance of dark green, while deficient leaves show by color, curves, lines, textures are visible symptoms (See Figure 1). These images must cover a range of lighting conditions, positions, and leaf ages to ensure strength of the model. To accurately recognize, detect, and predict nutrient deficiencies, deep learning research needs a large amount of data. In this research, having enough data to train the CNN model is critical, images of Eucalyptus leaf captured by a high-resolution camera and smartphone.

### 3.2. *Data Preprocessing*

Data preprocessing is a step of before training a CNN model, the purpose of this step is convert a raw image to the desired format of data for research improving the quality of data, In order to have a single leaf cropped and to have a region of interest, numerous photos with multiple leaves were taken during the data collection process in this study. The background's extraneous things were blurry. The gathered dataset thus has a distinct context. The raw images dataset required to be normalized because the raw data was too big for the computer to handle. Data standardization also helps to shorten the computing time needed for model training, as deep learning necessitates very powerful hardware.

Fig. 1. Images of Data Preprocessing

### 3.3. *Data Partitioning*

From the dataset, a training, validation, and testing set was produced. To recognize features in images, such as color, curves, lines, textures, and other aspects, the model is trained using the training set. The purpose of the validation set, sometimes called a development set, is to select the model, modify the hyperparameters, and evaluate the model. After selecting the model and hyperparameters, the test set is used to evaluate the performance of the proposed model on fictitious data. The data was divided 80-10-10 based on the literature review and experimentation [12]. 843 images constitute the total amount of data without partitioning; initially, 80% of the data are utilized for the training set, or a total of 674 images for all class; the remaining 10% are used to test the model. And 10% of the images are used for the validation set for each class.

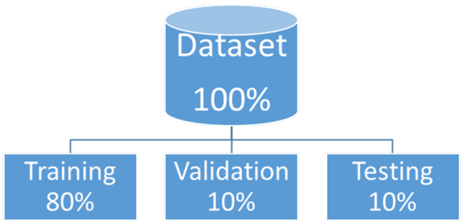


Fig. 2. The Data Partitioning

### 3.4. *Data Augmentation*

Profound understanding for a model to be adequately trained, CNN requires a big amount of datasets. A model will learn different sides of features from the image as the size of the dataset grows. Because CNN needs large amount of dataset. By doing this, the overfitting issue will be avoided and the model's performance will rise. A few thousand to millions of datasets make up the majority of widely used datasets for detection and classification. Therefore, the Keras class ImageDataGenerator is utilized, which facilitates the transformation of images in various formats, to artificially increase the number of image datasets. The ImageDataGenerator class accepts a number of arguments, some of which are Rotate_range: this function was used to rotate the source image at random between 0 and 180 degrees. Width_shift_range: utilized for arbitrary horizontal shift and displayed as an infraction of the total width Similar to the width shift range, the height shift range also operates with height. Zoom_range: an image's arbitrarly zooming range Horizontal_flip: this function flips an image horizontally at random.

### 3.5. *Model Design and Expirment*

When a selection of the model is compared to different algorithms, the deep learning model has performed well in a number of competitions, as numerous academics have noted. Experts' labor in selecting features is reduced by automatic feature selection from images, and a well-built deep neural network models can produce good results [13]. In tasks including, detection, classification, and others, the deep learning algorithm has demonstrated strong performance in the selected models of the Eucalyptus tree nutrition deficiency detection. Finally, the classification of images sampling in eight classes.

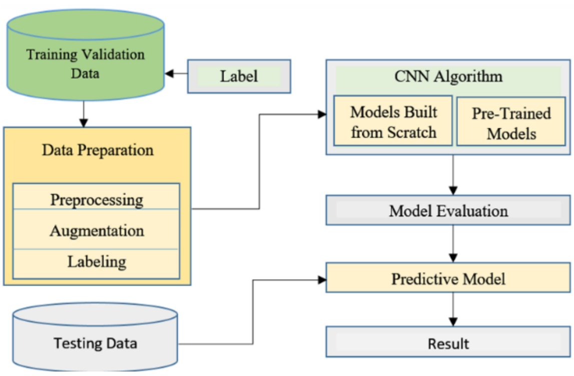


Fig. 3. System Architecture

### 3.6. *A Description of the Model Created from Scratch*

Using the various hyperparameters listed below, a first model was created from scratch to address our binary image classification challenge. The hyperparameter values that were tested in various scenarios. The input layer, which is the initial layer in the scratch model, accepts images with dimensions of 180 by 180 by 3.

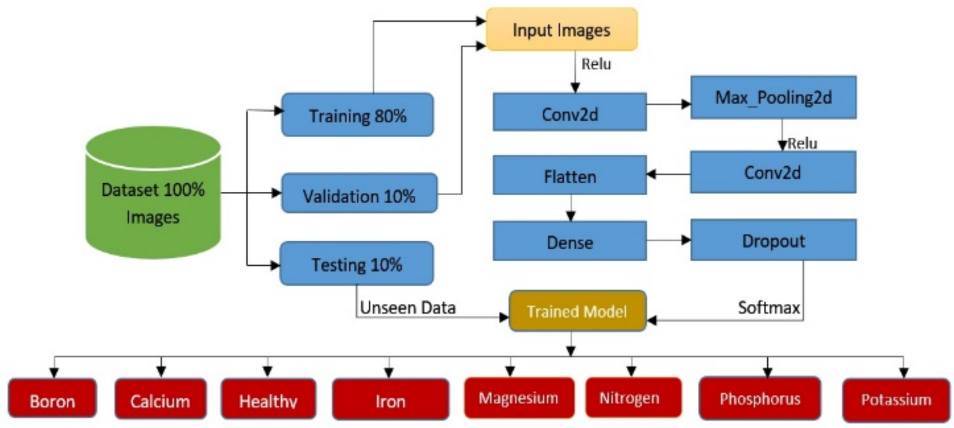


Fig. 4. Model from the scratch

### 3.7. *Pretrained Model Detection*

This study aims to detect nutrient deficiencies in Eucalyptus tree leaves, in this study applying four deep learning models like MobileNet, ResNet50, DenseNet, and Inceptionv3. Decide on the model in terms of accuracy, computational efficiency, and deployment constraints to compare different deep learning architectures for accurate detection of nutrient deficiency in Eucalyptus leaves. Each of these models has been widely used and studied, with pre-trained models in the deep learning frameworks TensorFlow and PyTorch.

**MobileNet** is designed to be lightweight and efficient it achieves this by employing separable convolutions based on depth, which reduce the computational cost significantly while maintaining good accuracy.

**ResNet50** (Residual Network) is known for its depth, utilizing jump over certain layers by skipping connections or shortcuts. ResNet50 allows for very deep networks to be trained effectively. Its architectures are used as feature extractors in various computer vision tasks.

**DenseNet** This dense connectivity pattern promotes feature reuse, strengthens feature propagation, and reduces the number of parameters. DenseNet architectures are particularly effective for tasks with limited data or computational resources, where datasets are often small.

**Inception v3**, also known as GoogLeNet v3, It is characterized by its inception modules, which consist of parallel convolutional layers of different sizes. These modules allow the network to capture features at multiple scales efficiently. Inception v3 balances model complexity and performance and is often used in applications where both accuracy and computational efficiency are crucial.

## 4. Result and Discussion

### 4.1. *Findings from the Experiment*

The suggested model can identify the symptom to determine if the provided leaf image is healthy or Boron, Calcium, Iron, Magnesium, Nitrogen, Potassium, Phosphorus nutritional deficiency based on a different input images. Four scenarios were employed in the experimental process to solve the problem using this model. This pretrained models are MobileNet, ResNet50, DenseNet, and InceptionV3. During training the neural network models, the models experimented with various hyperparameters such as the activation function, learning rate, optimization technique, loss function, and batch size. MobileNet is lightweight and computationally efficient, while ResNet50 is designed to enables deep feature learning through residual connections. DenseNet improves feature reuse and pitch flow by densely connecting layers densely, whereas InceptionV3 captures multi-scale features using parallel convolution operations. These different architectural setups allow us to make a fair comparison and figure out which model works best for spotting nutrient deficiencies in Eucalyptus leaf images. The accuracy plot really brings this to life; it shows both training and validation accuracy climbing steadily over time, a clear sign that the model is learning well and generalizing effectively. Plus, the gap between the two stays small, which tells us the model is stable and not overfitting when it comes to identifying those deficiencies.

### 4.2. *Pretrained Models for Deep Learning*

The pretrained model MobileNet, ResNet50, DenseNet, and InceptionV3 were used for training and testing a model with the same hyperparameter setting configured. The activation function, learning rate, epoch, batch size, loss function, and optimization algorithm are the hyperparameters of the CNN algorithms that have been experimented with varying values. The performance of the proposed models was evaluated using accuracy, precision, and recall. The evaluation was conducted on the test dataset of Eucalyptus leaf images, and the results obtained from the custom CNN and pretrained models are summarized in Table 1.

Table 1. Classification Matrices

| Hyperparameters | Value | Models |
|---|---|---|
| Activation Function | Sigmoid, Softmax | |
| Learning Rate | 0.00002, 0.0001 | MobileNet, ResNet50, DenseNet, InceptionV3 |
| Epoch | 20, 30, 50 | |
| Dropout | 0.5, 0.3 | |
| Optimization Algorithm | RMSprop, Adam | |

### 4.3. *Purpose Model for Eucalyptus Nutrition Deficiency*

Google created an effective Inception CNN architecture, as a Googlenet. It contains many layers, with many neurons within each layer. This deep learning trained model can function well with severe memory limitations and additional resources for computing. One benefit of the pretrained model is its low computational cost when compared to high performance successors [14].

### 4.4. *Identification Outcome of the Proposed Model*

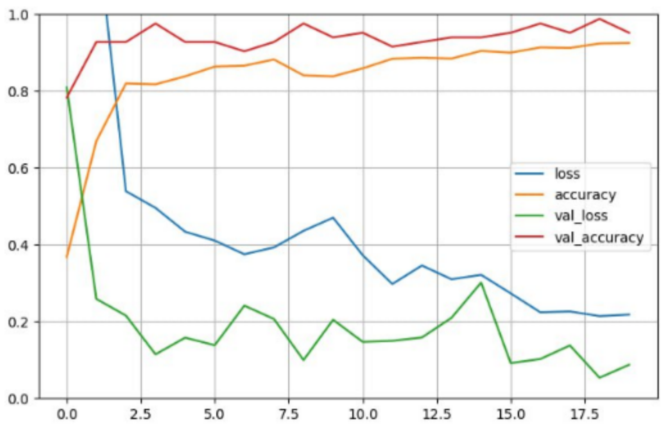


Fig. 5. MobileNet: Accuracy 89.09, Val_Accuracy 98.80, Val_Loss 0.7627, Loss 5.3155, Dropout 0.3, Epoch 20

### 4.5. *Utilizing the Proposed Model*

In this study, deep learning models including MobileNet, ResNet50, DenseNet, and InceptionV3 are examined. These models were taken into consideration in this study due to their various performance and practical application strengths. Specifically, deployment constraints, the degree of computational efficiency needed, and the precision necessary for the classification task can all effect the choice of these models. In the context of the study, each of these architectures offers a distinct balance between computational cost and predictive capability, making them appropriate for comparison and assessment. Additionally, these models are popular in the deep learning research domain and are supported by pre-trained weights that are easily accessible in well-known frameworks like PyTorch and TensorFlow, which makes it easier to install and modify them for the study.

### 4.6. *Utilizing a Model Created from Scratch to Identify Eucalyptus Nutrition Deficiency*

The experiment started by creating a CNN model and comparing it to other pre-trained models before utilizing the pretrained model. It has good training and validation accuracy and testing results, using RMSprop and Adam with the specified learning to identify. Building a model from scratch has the disadvantage of requiring a large amount of data, as the model's performance is dependent on it. The model, which was created.

## 5. Conclusion

The use of deep learning convolutional neural networks (CNNs) including MobileNet, ResNet50, DensNet, and InceptionV3 has demonstrated encouraging outcomes in identifying nutritional deficiency in the leaves of Eucalyptus tree. These algorithms show promise in correctly diagnosing and classifying different nutrient shortages based on leaf images, with a validation accuracy of 98.80 attained. This achievement highpoints CNNs' potential for accuracy agriculture, particularly for non-invasive, distant plant health diagnosis. This study explores in deep learning the use of Convolutional Neural Networks (CNNs) to identify nutritional deficiencies in Eucalyptus tree using the image of leaves. The research uses CNN algorithm and pre-trained models. These are MobileNet, ResNet50, DensNet, and InceptionV3 for precise analysis and classification. The study demonstrates the efficiency of deep learning techniques in addressing agricultural challenges and compares the effectiveness of various CNN algorithms. Finally, we developed a models and the model can detect and classify nutrient shortages in Eucalyptus tree, enabling timely corrective steps, increased crop productivity, better plant health, and sustainable farming methods. In this study we suggest, the feature researcher can increase the dataset and improve the performance of the model. Also, we recommend the researcher can do for the remaining Eucalyptus trees nutrient deficiency using different algorithms and mobile-based systems. Also, we recommend using drone technology is preferred for image capturing. In addition to this, developing a model for other plant nutrient deficiency detection is the best option to keep the healthy plants.

## References

1. Amanpreet Kaur1, and Rajesh Monga, "Eucalyptus Trees Plantation: A Review on Suitability and their Beneficial Role," *International Journal of Bio-resource and Stress Management*, february 2021.
2. Mesfin Abebe, Wubalem Tadesse, "Eucalyptus in Ethiopia Risk or Opportunity?," *http://www.eiar.gov.et ISBN: 978-99944-53-91-4*, p. 1, 2014.
3. Belay Zergaa,c, Bikila Warkineh, Demel Teketay, Muluneh Woldetsadik, Mesfin Sahle, "Land use and land cover changes driven by expansion of eucalypt plantations in the Western Gurage Watersheds, Centeral-south Ethiopia," *Elsevier*, 2021.

4. G. Kaur, "AUTOMATED NUTRIENT DEFICIENCY DETECTION IN PLANTS: A REVIEW," *Palarch's Journal Of Archaeology Of Egypt/Egyptology 17(6). ISSN 1567-214x*, p. 1, (6) (2020).
5. S. Jeyalakshmi, R. Radha, "A Review on Diagnosis of Nutrient Deficiency Sympto,s n Plant Leaf Image Processing," *ICTACT JOURNAL ON IMAGE AND VIDEO PROCESSING*, vol. VOLUME: 07, no. ISSUE: 04, p. 1, MAY 2017.
6. Betania Vahl de Paula 1, , Wagner Squizani Arruda 1, Léon Etienne Parent 1,2 ,Elias Frank de Araujo 3 and Gustavo Brunetto 1, "Nutrient Diagnosis of Eucalyptus at the Factor-Specific Level Using Machine Learning and Compositional Methods," *MDPI*, August 2020.
7. Leeth Singh1, Onisimo Mutanga1, Paramu Mafongoya1, Kabir Peerbhay1,2, Steven Dovey2, "Detecting nutrient deficiencies in Eucalyptus grandis trees using hyperspectral remote sensing and random forest," *ResearchGate*, August 2021.
8. Anu Jose1,3, S Nandagopalan2,4 , Vidya Ubalanka1,5 and Dhanya Viswanath1,6, "Detection and classification of nutrient deficiencies in plants using machine learning," *Journal of Physics*, 2020.
9. S. Jeyalakshmi1 and R. Radha2, "A REVIEW ON DIAGNOSIS OF NUTRIENT DEFICIENCY SYMPTOMS IN PLANT LEAF IMAGE USING DIGITAL IMAGE PROCESSING," *ICTACT*, vol. VOLUME: 07, no. ISSUE: 04, MAY 2017.
10. Carlos Antonio da Silva Junior a, Paulo Eduardo Teodoro b,, Larissa Pereira Ribeiro Teodoro b,, "Is it possible to detect boron deficiency in eucalyptus using hyper and multispectral sensors," *Elssevier*, 2021.
11. Xiaohui Yang, Fang Xu, Wen Pan, Weihua Zhang, Huanqin Liao, Baozhu Zhu, Bin Xu, Xinyu Chen and Huixiao Yang, "Comparative Transcriptome Analysis of High- and Low-Growth Genotypes of Eucalyptus urophylla in Response to Long-Term Nitrogen Deficiency," *MDPI*, 30 December 2023.
12. Yazid Aufar1,Muhammad Helmy Abdillah2,Jiki Romadoni3,, "Web-based CNN Application for Arabica Coffee Leaf Disease Prediction in Smart Agriculture," *http://jurnal.iaii.or.id*, vol. Volume 10 Number 1 of 2026, 2021.
13. Rammah Yousef1,Gaurav Gupta1,Nabhan Yousef2,Manju Khari3, "A holistic overview of deep learning approach in medical imaging," *under exclusive licence to Springer-Verlag GmbH Germany*, 21 January 2022.
14. Jahandada, Suriani Mohd Sama, Kamilia Kamardinb, Nilam Nur Amir Sjarif, Norliza Mohamed, "Neural Network (CNN) Architectures GoogLeNet Inception-v1 and Neural Network (CNN) Architectures GoogLeNet Inception-v1 and Inception-v3," *ScienceDirect*, 2019.