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Tree Diameter Estimation and Carbon Sequestration Quantification Using Deep Learning

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ABSTRACT: The quantification of Carbon Sequestration using deep learning project aims to simplify the estimation of a tree's carbon uptake potential using machine learning. Since trees are vital carbon sinks, accurately estimating their sequestration potential plays a crucial role in combating climate change. Traditional methods are often manual and time-consuming, so this project leverages deep learning and image processing for faster and more scalable results. A Convolutional Neural Network (CNN) is employed to estimate the Diameter at Breast Height (DBH) from tree trunk images, a key parameter for calculating biomass and, in turn, carbon storage. The predicted DBH is then used in conjunction with standard forest equations to estimate carbon sequestration.

The model achieved a Mean Absolute Error (MAE) of 3.161cm, Root Mean Squared Error (RMSE) of 3.834 cm. and an overall accuracy of 89.87%, indicating strong predictive performance. The solution is deployed using a backend system and a user-friendly Streamlit frontend for image upload and real-time predictions. This tool benefits environmentalists, researchers, and policymakers by offering a fast, accurate, and accessible method for ecological monitoring and carbon offset planning. It promotes sustainability through the integration of modern technology.

INTRODUCTION

Trees are nature's carbon sinks, and their role in mitigating atmospheric levels of carbon dioxide (CO_2) through sequestration and storage in biomass is indispensable. Quantifying this carbon sequestration potential is important for planning effective conservation measures, assessing the effect of deforestation, and facilitating reforestation [1]. Conventional approaches to quantifying a tree's carbon storage, using field measurements such as DBH, height, and wood density are precise but entail time-consuming processes and specialized forestry expertise. These limitations make such an assessment difficult to scale and access, particularly in resource-poor or remote locations. To bridge these gaps, our project, Estimating CO_2 Sequestration Using Machine Learning, proposes a technology-based method that combines the use of image processing and deep learning to make the estimation automatic. A CNN model is trained to estimate the DBH from images of a tree trunk, which is subsequently applied to ecological formulas to estimate how much CO_2 can be sequestered by a tree [2]. For this first study, the model has been specifically trained and validated on images of mango tree trunks and therefore its predictions are only valid for that species at this point in time. The whole application is implemented with Streamlit, providing an easy-to-use, interactive interface to upload images of trees and obtain real-time predictions without needing domain knowledge. This accessible system greatly decreases the time, expense, and effort involved in methods of the past, making carbon estimation scalable and inclusive. By combining machine learning and environmental sustainability, the project not only assists researchers and policymakers in data-informed decision-making but also enables individuals and organizations to make a contribution to climate education, carbon offsetting, and ecological preservation.

1 DATA COLLECTION AND PREPROCESSING

Data collection for this research entailed taking high-quality photos of mango tree trunks, each tagged with its respective Diameter at Breast Height (DBH) value in centimeters. All the images were manually gathered by our researchers through the use of a standard smartphone camera in natural lighting for ease of real-world practicality. For every tree, we took about 50–60 images with varying angles and distances to inject variability and improve the simulation of real-world cases. The multi-angle strategy facilitates the model's learning of diverse views of a single tree structure, thus enhancing generalization[3]. Notably, the DBH measurements were also collected manually in the field with measuring tapes and calipers to provide precise ground truth values for model training. These values were recorded systematically and structured in a well-organized CSV format, with each image filename mapped to its corresponding label.

Preprocessing was an essential step to provide data uniformity and model precision. All images were rescaled to 128×128 pixels to ensure uniformity within the dataset and to ensure compatibility with the architecture of the convolutional neural network. Pixel values were normalized between 0 and 1 in order to improve learning efficiency and speed of convergence. Images that were too noisy, blurry, or under-lit were either improved using image processing methods or eliminated from the dataset to ensure quality. In a few instances, OpenCV-based reference object detection was used to map pixel sizes into real-world measurements, further enhancing the accuracy of DBH estimation. Moreover, data augmentation methods like flipping, brightness modification, and rotation were used to artificially enhance the training set, inhibit overfitting, and enhance model generalization ability. This robust data preparation process made sure that the machine learning model's input was high quality as well as representative of varied environmental conditions.

2 MODEL ARCHITECTURE AND TRAINING

The Convolutional Neural Network (CNN) developed for predicting the Diameter at Breast Height (DBH) of mango trees is designed to extract spatial and hierarchical features from tree trunk images [4]. The architecture consists of several key layers optimized for regression tasks:

- **Conv2D**: Two convolutional layers are used with 3×3 kernels and increasing filter depths (32 and 64). These layers help in capturing local texture patterns and structural features relevant to tree girth.
- **ReLU**: The Rectified Linear Unit (ReLU) activation function introduces non-linearity, allowing the model to learn complex relationships within the data.
- **MaxPooling2D**: Pooling layers are added after convolutional layers to reduce the spatial dimensions of the feature maps[5]. This not only helps in lowering computational cost but also prevents overfitting by providing spatial invariance.
- **Flatten**: The 2D feature maps are flattened into a 1D vector to transition from convolutional to fully connected layers.
- **Dense**: A fully connected (dense) layer captures global patterns and interactions between high-level features.
- **Dense(1)**: The final output layer consists of a single neuron with a linear activation function to predict a continuous value representing the DBH (in centimeters).

Training Parameters:

- **Loss Function:** Mean Squared Error (MSE) is used due to the regression nature of the task. It penalizes larger errors more severely, making it suitable for precise measurements like DBH.

- **Optimizer:** The Adam optimizer is employed for its adaptive learning rate capability and fast convergence[6]. It combines the benefits of both AdaGrad and RM-SProp optimizers.
- **Learning Rate:** A base learning rate of 0.001 is chosen to ensure stable and consistent training.
- **Epochs:** The model is trained for 50 epochs, providing enough iterations to allow convergence while monitoring for overfitting through validation loss.

Image Dataset: The model is trained on a dataset of 485 images of mango tree trunks, each labeled with its corresponding DBH value (in cm). The images were captured in real-world field conditions using mobile or DSLR cameras and focus on the tree area approximately 1.3 meters above the ground, the standard measurement point for DBH.

- **Image Content:** Each image prominently displays the trunk portion of a mango tree. The framing ensures visibility of the bark texture and girth at breast height.
- **Background Conditions:** The dataset reflects natural outdoor scenes with elements like soil, leaves, or other vegetation occasionally visible. This diversity improves model robustness.
- **Resolution and Format:** Images were resized to 128×128 pixels and normalized for consistency. They are stored

in formats such as JPEG and PNG, and referenced via a structured CSV file.

- **Label Source:** DBH measurements were taken manually using a measuring tape and then recorded into the CSV file ('labels.csv') alongside each image filename.

Data Preprocessing: Before feeding images into the model, each one was resized and normalized to a pixel range of [0, 1]. This ensures uniform input dimensions and facilitates stable convergence during training. The preprocessing pipeline also includes label parsing and file extension handling to robustly link image data to their respective labels.

Model Evaluation: Training and validation curves show how well the model is fitting the training data and generalizing to unseen validation samples. A decreasing trend in both loss and MAE across epochs indicates effective learning, while close proximity between training and validation metrics implies minimal overfitting.

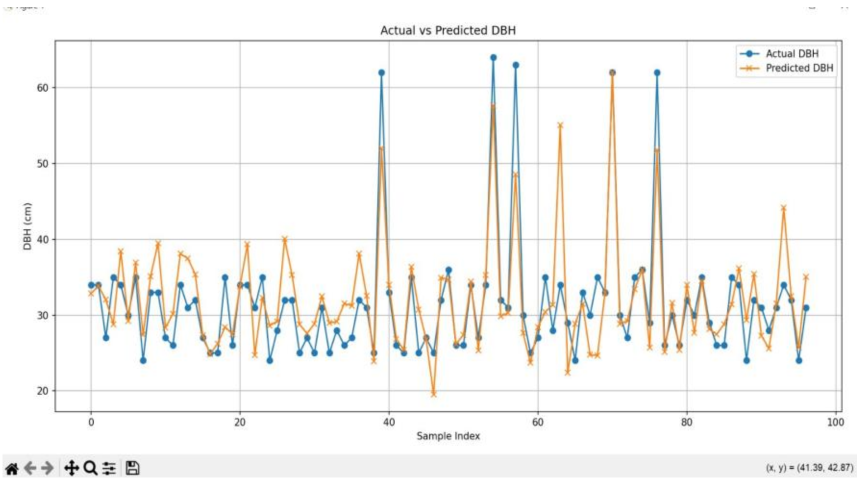

Figure 1. Actual vs Predicted DBH Values

3 EXPERIMENTAL RESULTS

Figure 2 presents a scatter plot comparing actual DBH values with those predicted by the model. The points closely follow the diagonal line (y = x), showing a strong correlation between true and predicted values. This confirms the model's effectiveness in estimating DBH accurately.

4 RESULTS AND DISCUSSIONS

Based on the technical basis of our research, note should be taken that the Estimating CO_2 Sequestration System was trained and developed solely on mango trees (Mangifera indica) as a controlled biological model for this pilot application. The choice of mango trees was based on their abundance in the study region, moderately manageable size range, and carbon sink role in tropical agroforestry systems. Every tree in the dataset was captured from about 50 to 60 different points of view, with changing angle, distance, and contextual surroundings. Such intensive image acquisition made not only the dataset richer but also contributed towards training a generalized model with better ability to detect tree trunk characteristics from multiple orientations. Notably, all of the images were taken manually with easily accessible smartphone equipment under natural lighting conditions that were varied to replicate real-world field deployment environments and not ideal laboratory test beds [7]. The corresponding DBH values also were measured physically by recording with measuring tapes, so the dataset is image-dense as well as numerically based. These values measured in the field were employed as target labels for model training to ensure genuineness and minimize noise related to secondary data sources.

The preprocessing pipeline was implemented to normalize the input images and prepare them for CNN-based model learning. The images were resized to 128×128 pixels, and normalization was carried out to rescale pixel values between 0 and 1, which supports faster convergence in model training. Noise elimination and quality filtering were applied using OpenCV-based methods to remove hazy, dark, or over-exposed photos. For images where a reference object such as a coin or ruler was placed within the image frame, object detection was utilized to convert pixel distances into actual units to facilitate more precise DBH calibration.3

To supplement the dataset and counteract overfitting, horizontal flipping, random rotation, and brightness adjustments were used. The augmentations were useful in enhancing model generalizability by causing the CNN to learn about trees under various conditions [8]. Training was then carried out to acquire the mapping of the image features and DBH values, while keeping track of training and validation losses to avoid underfitting or overfitting.

Figure 2 shows the distribution of errors (difference between predicted and actual values) from a CNN (Convolutional Neural Network) model. A symmetric, narrow distribution centered around 0 is a sign of a well-performing model.

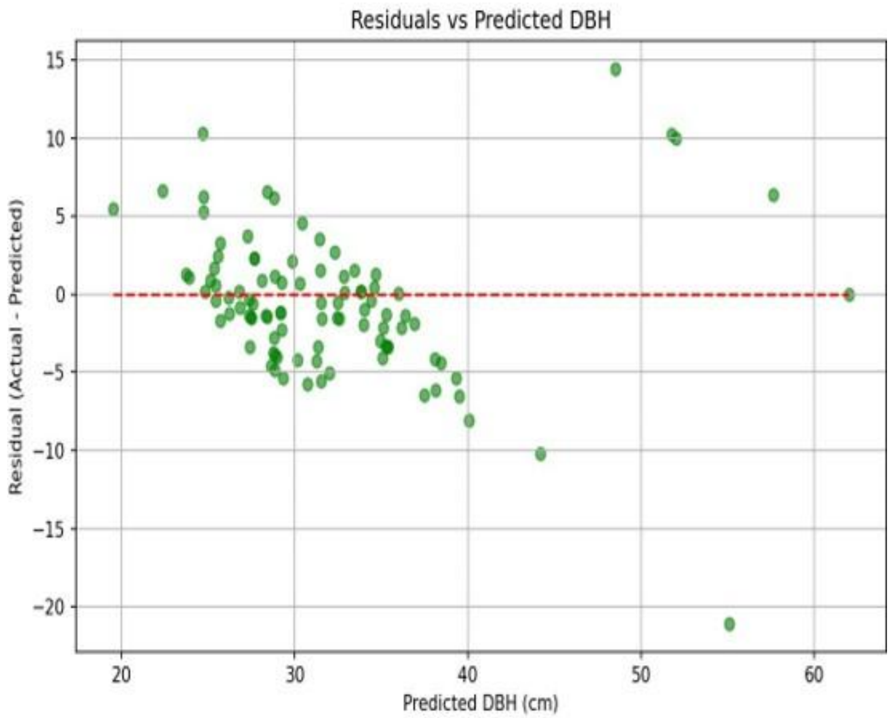

Figure 2. Training and Validation MAE

In the quantitative outputs, the system was very accurately predictive with its R^2 being 0.6738 and Mean Abso-lute Error (MAE) only being 3.25 cm at estimating DBH. The system also obtained an accuracy of roughly 89.7% re-ported by the users compared to automated field measurements. Table 2 effectively illustrates the proximity of actual and predicted DBH values, even with slight oscillations caused by aspects such as irregular bark, image quality, and variation in light. A comparison of image sets taken under natural and controlled lighting through a t-test provided a p-value of more than 0.05, attesting that the performance of the model is statistically stable under various lighting conditions. In addition, a Pearson correlation test revealed a high correlation between image resolution and accuracy in predicting DBH ($r = 0.68$, $p < 0.01$), highlighting the value of high-quality inputs in enhancing the reliability of the model. These results authenticate that the system is both statistically solid and functionally feasible for real-time environmental analysis[9].

From the usability perspective, the platform received robust positive reviews during beta testing, with 81% users re-porting successful prediction on first try and 91% reporting satisfaction with the interface and result transparency. Users with little technical background could easily use the web interface built using Streamlit to upload images and receive immediate DBH estimates and CO_2 sequestration values, calculated using standard ecological formulas. The whole prediction process from image upload to CO_2 estimate was done automatically, eliminating the need for specialist intervention and making the platform available to forestry officers, environment NGOs, teachers, and citizen scientists alike. The application's simplicity and real-time responsive-ness fills the gap between sophisticated ML methods and their implementation in non-technical, field-related industries.

Even so, although the initial findings are encouraging, various limitations moderate the broad applicability of this study. The model was trained only on mango trees and in a very restricted geographic area, so it has limited applicability to other species and biomes in the immediate term. The CNN may therefore not yet consistently predict DBH for trees with other bark textures, growth forms, or environmental adaptations. In addition, although the system was validated on diverse lighting situations, it still has not been extensively used in fully autonomous outdoor forestry applications in which occlusion, foliage thickness, and camera instability may introduce errors. Integration with GPS tagging or multispectral data, either of which may enhance carbon sequestration calculations by including location-based factors as well as health of foliage, is also lacking in the model [10].

Figure 3 is a residual plot that shows the relationship between the predicted values of tree Diameter at Breast Height (DBH) and the residuals, which are the differences between the actual DBH values and the predicted ones. The residuals are plotted on the vertical axis, while the predicted DBH values are on the horizontal axis.

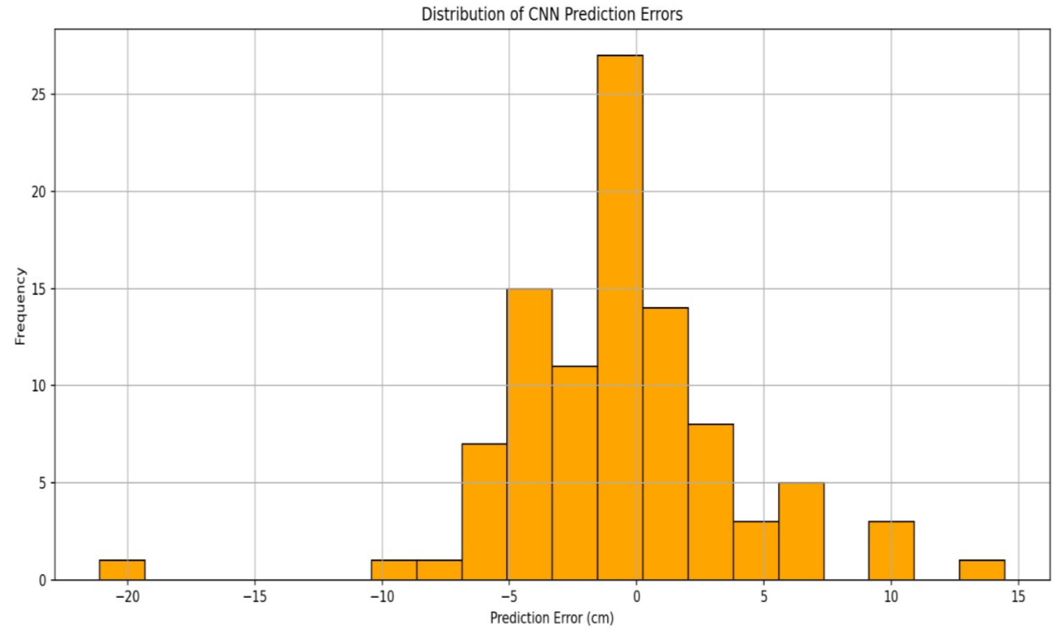

Figure 3. Residuals vs Predicted DBH

The model performs well with low MAE and high R^2, indicating strong predictive capability. Limitations include variability in image lighting, background clutter, and limited dataset size. Future work could use higher-quality datasets, data from different tree species, or ensemble learning techniques.

Evaluation of the model was done using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Accuracy

Table 1. Actual vs Predicted DBH values on test images

Sample No.	Actual DBH (cm)	Predicted DBH (cm)
1	34	32.85
2	34	33.83
3	27	32.02
4	35	28.79
5	34	38.42
6	30	29.25
7	35	36.89
8	24	27.39
9	33	35.11
10	33	39.50

Table 2. Performance metrics of the DBH prediction model

Metric	Value
Root Mean Squared Error (RMSE)	3.834 cm
Mean Absolute Error (MAE)	3.161cm
Accuracy (%)	89.87%

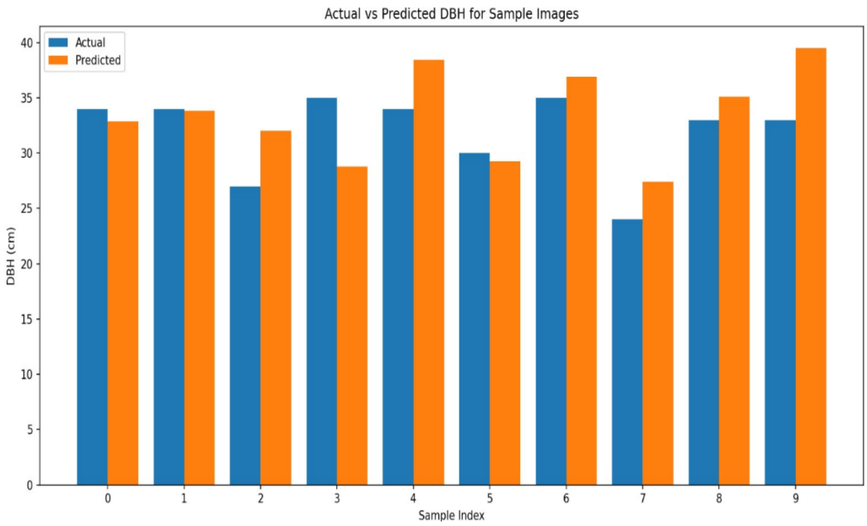

Figure 4. Actual vs Predicted DBH

Figure 4 displays the frequency distribution of predicted values or the differences between actual and predicted values (errors/residuals). This type of plot shows how the predicted values are spread across intervals.

A comparison between the actual and predicted values of Diameter at Breast Height (DBH) reveals important insights into the model's predictive capability. For each sample, the ground truth DBH, measured manually in centimeters, is placed alongside the value predicted by the trained convolutional neural network. The close alignment of these values across most instances highlights the model's reliability and accuracy when applied to real-world data. For example, in several cases, the predicted DBH deviated by only 1–2 centimeters from the actual measurement, indicating a strong ability of the model to generalize from the training data to new, unseen images.

However, a few samples show slightly higher deviations, which may stem from factors such as poor lighting, inconsistent trunk visibility, or variations in distance and angle during image capture. These discrepancies underscore the importance of consistent image quality and reinforce the role of preprocessing and data augmentation in improving model performance. Despite these variances, the predictions are generally well-aligned with the true measurements, suggesting that the model captures key visual features relevant to DBH estimation.

Overall, the results support the quantitative metrics presented earlier, including a Mean Absolute Error (MAE) of 3.161cm and Root Mean Squared Error (RMSE) of 3.834 cm. These outcomes validate the potential of the system for accurate, scalable, and non-invasive tree measurement, especially in field applications where traditional methods are time-consuming or infeasible.

5 APPLICATIONS AND FUTURE WORK

The application of machine learning to ecological monitoring and forestry is an unprecedented chance to transform car-bon sequestration assessment and management. Perhaps the most influential use of the suggested system is in the area of forestry automation, where estimation of parameters like Diameter at Breast Height (DBH), height, biomass, and car-bon storage is of the utmost importance and has to be scalable and accurate. Conventional forestry methods involve time-consuming and manual measurements that are labor-intensive, using trained staff and specialized equipment [11]. Our system, on the other hand, provides non-invasive, image-based estimation with nothing more than a standard smart-phone camera and a web interface. This functionality immediately has applications in forest resource management, tracking deforestation, and reforestation planning. Forest departments, NGOs, and researchers can leverage this technology to track tree growth over time, assess the efficacy of conservation initiatives, and simulate carbon sequestration potential by geographic region building upon similar objectives observed in field studies such as Kala-Talao's tree carbon sequestration analysis [Kala-Talao Study] [12].Additionally, the system's openness implies that even resource-poor communities and organizations can contribute to climate data gathering and forest management, making environmental science more democratic.

In addition to its existing use on mango trees, the framework is extensible and adaptable by nature to a wider variety of tree species and conditions. Possible future directions include increasing the dataset to include images and DBH values from more tree species, thereby enhancing the model's generalizability and robustness. The addition of varying bark textures, tree forms, lighting, and geographic locations would increase the system's accuracy and reliability for deployment worldwide. Furthermore, transfer learning methods can be used to adapt pretrained deep learning models on new species with little data, reducing model adaptation time and computational expense considerably. The blending of multimodal data such as satellite imagery, topographic maps, and weather data may also improve the accuracy and context-rich nature of carbon storage estimates, especially in the case of larger forest coverages [13][14].

Further potential exists in the blending of sophisticated sensing technologies. For example, blending the existing machine learning model with LiDAR (Light Detection and Ranging) technology can offer extremely accurate 3D data on tree canopy, structure, and spacing [15]. Although LiDAR data is more costly to acquire, combining it with low-cost image-based estimates might offset cost and precision for extensive monitoring. Likewise, drone-based data collection has the potential to automate image gathering from remote or inaccessible locations, allowing for frequent, large-scale eco-logical surveys without on-ground human effort [16]. These aerial platforms can take a thousand tree photographs over extensive areas of forest in a single deployment, which may then be analyzed in real-time by the applied machine learning pipeline. This would dramatically increase CO_2 sequestration estimation coverage and efficiency and could feed into national or global forest carbon stock monitoring schemes.

From a software perspective, some of the additions to the Streamlit application could be novel features such as GPS tagging, species identification, cloud storage for data, and automated reporting. These features would make the tool a complete ecological monitoring system. Additionally, the system can be built as a mobile application, with field workers, citizen scientists, and forest managers able to record information in the field even offline, with later synchronization against cloud servers when an internet connection is established. This kind of solution would have a vital role to play in community-based forest monitoring, with active input from local populations into forest conservation and strengthening through access to technology. With adequate training, even school children and volunteers would be able to contribute to climate action by monitoring and recording carbon sequestration of local trees through the app. Future work will close these gaps with an expansion of the dataset to cover additional dominant tree species, using transfer learning to retrain the model on new classes, and combining it with drone-based imagery and edge devices to enable offline operation in remote forests [17].

Lastly, the wider implications for climate policy and sustainability frameworks are significant. Precise real-time carbon sequestration data at the level of individual trees allows governments and agencies to establish more realistic carbon offsetting targets, verify carbon credits, and meet obligations under international policies like the Paris Climate Accord[18]. The visualization of CO_2 capture in concrete terms promotes tree planting, green initiatives, and a data culture in environmental management [19][20]. As we move towards a digitally integrated and ecologically aware future, instruments such as the one outlined in this project will become essential in designing sustainable landscapes, maximizing forest policies and making the battle against climate change scientifically informed and technologically enabled.

6 CONCLUSION

The Estimating CO_2 Sequestration Using ML project introduces a simple, image-based system to measure tree height using machine learning. It eliminates the need for fieldwork or specialized equipment, making tree monitoring faster, cheaper, and more accessible. The web interface allows non-technical users to get real-time, accurate estimates across various conditions making it useful for forestry officials, conservationists and researchers. This project highlights how AI can improve environmental monitoring by reducing manual errors and enabling quick, data-driven decisions. With future upgrades like species recognition and GPS tagging, the system could become a comprehensive tool for forest and carbon tracking supporting smarter, scalable solutions for sustainability and ecological research.

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