algorithms

MDPI

Article

Environmental Sensitivity in AI Tree Bark Detection: Identifying Key Factors for Improving Classification Accuracy

Charles Warner [1], Fanyou Wu [1], Rado Gazo [1,*], Bedrich Benes [2] and Songlin Fei [1]

[1] Department of Forestry and Natural Resources, Purdue University, West Lafayette, IN 47906, USA; warner88@purdue.edu (C.W.); fanyou.wu@outlook.com (F.W.); sfei@purdue.edu (S.F.)

[2] Department of Computer Science, Purdue University, West Lafayette, IN 47906, USA; bbenes@purdue.edu

* Correspondence: gazo@purdue.edu; Tel.: +795-494-3634

Abstract

Accurate tree species identification through bark characteristics is essential for effective forest management, but traditionally requires extensive expertise. This study leverages artificial intelligence (AI), specifically the EfficientNet-B3 convolutional neural network, to enhance AI-based tree bark identification, focusing on northern red oak (*Quercus rubra*), hackberry (*Celtis occidentalis*), and bitternut hickory (*Carya cordiformis*) using the CentralBark dataset. We investigated three environmental variables—time of day (lighting conditions), bark moisture content (wet or dry), and cardinal direction of observation—to identify sources of classification inaccuracies. Results revealed that bark moisture significantly reduced accuracy by 8.19% in wet conditions (89.32% dry vs. 81.13% wet). In comparison, the time of day had a significant impact on hackberry (95.56% evening) and northern red oak (80.80% afternoon), with notable chi-squared associations ($p < 0.05$). Cardinal direction had minimal effect (4.72% variation). Bitternut hickory detection consistently underperformed (26.76%), highlighting morphological challenges. These findings underscore the need for targeted dataset augmentation with wet and afternoon images, alongside preprocessing techniques like illumination normalization, to improve model robustness. Enhanced AI tools will streamline forest inventories, support biodiversity monitoring, and bolster conservation in dynamic forest ecosystems.

Keywords: dendrology; artificial intelligence; deep learning; convolutional neural networks

Academic Editors: Marcin Iwanowski and Bogusław Cyganek

Received: 21 May 2025
Revised: 21 June 2025
Accepted: 5 July 2025
Published: 8 July 2025

Citation: Warner, C.; Wu, F.; Gazo, R.; Benes, B.; Fei, S. Environmental Sensitivity in AI Tree Bark Detection: Identifying Key Factors for Improving Classification Accuracy. *Algorithms* **2025**, *18*, 417. https://doi.org/10.3390/a18070417

1. Introduction

Accurate tree species identification through bark characteristics is a vital skill for foresters, enabling precise differentiation critical for effective forest management. There are many ways to identify trees, including leaves, fruit, and bark [1]. Traditionally, this expertise demands years of experience and advanced training, limiting its accessibility. Recent advancements in artificial intelligence (AI), particularly deep learning and convolutional neural networks (CNNs), offer the potential to replicate this precision with automated, rapid, and remote identification tools [2]. This project aims to develop AI-based tree bark identification tools to streamline digital forestry and support conservation efforts without requiring extensive professional training.

Deep learning has enabled human-like pattern recognition by learning from large, labeled datasets [3]. In tree bark identification, CNNs have demonstrated accuracy comparable to or surpassing traditional texture classification methods, with straightforward implementation and end-to-end training [1,4,5]. However, existing datasets, such as BarkTex [6], Trunk12 [7], and BarkNet 1.0 [4], which provide labeled bark images of hardwood species across the United States, Canada, and Europe, are limited by variability in scope, species diversity, and accessibility [8]. These constraints hinder comprehensive AI training, resulting in identification systems that currently underperform compared to experienced foresters.

To address these limitations, this study leverages the CentralBark dataset [9], which includes over 19,000 images of 25 commercially valuable hardwood species from the Central Hardwood and Central Appalachian regions, accompanied by metadata such as diameter at breast height (DBH), bark moisture content (wet or dry), GPS location, timestamp, date, and camera settings [9]. We are focusing on a new, smaller three-species dataset separate from the CentralBark dataset—northern red oak, hackberry, and bitternut hickory. We are calling this new dataset CBDS_Small. This research investigates the impact of three key variables contributing to inaccuracies in AI-based bark identification: (1) time of day (affecting lighting conditions), (2) bark moisture content, and (3) cardinal direction of observation (north, south, east, or west). Identifying primary sources of error will guide improvements in data collection and preprocessing, such as standardizing image capture protocols or augmenting datasets with underrepresented conditions.

By enhancing the robustness of deep learning models, this work aims to develop reliable AI tools for real-world forestry applications, where environmental variability is a common occurrence. Improved bark identification systems will streamline forest inventory processes, enable precise monitoring of species diversity and health, and support sustainable forest management.

2. Materials and Methods

2.1. Study Area

Data collection for CBDS_Small was conducted in two forested areas near West Lafayette, Indiana, USA, which were selected for their ecological suitability as habitats for the target tree species and for their accessibility for field research. These sites, depicted in Figure 1, provide diverse forest conditions representative of the Central Hardwood region, ensuring robust data collection across varying environmental contexts. The primary site, Celery Bog Nature Area, is a public nature center located northwest of Purdue University campus at 1620 Lindberg Road, West Lafayette, IN 47906. This 195-acre wetland and forest ecosystem supports a rich diversity of hardwood species, including northern red oak, making it an ideal location for studying bark characteristics under natural conditions. The second site, Richard G. Lugar Forestry Farm, is located west of the campus at 555 North Sharon Chapel Road, West Lafayette, IN 47906. This 120-acre research facility, managed by Purdue University, features managed forest plots with mature hardwood stands, offering a controlled yet naturalistic setting for data collection. Both sites were chosen to capture images of northern red oak (*Quercus rubra*), hackberry (*Celtis occidentalis*), and bitternut hickory (*Carya cordiformis*), species prevalent in the region and critical for commercial and ecological purposes. The selection of these locations ensures that the collected data reflect real-world forest conditions, enhancing the applicability of findings to regional forest management practices.

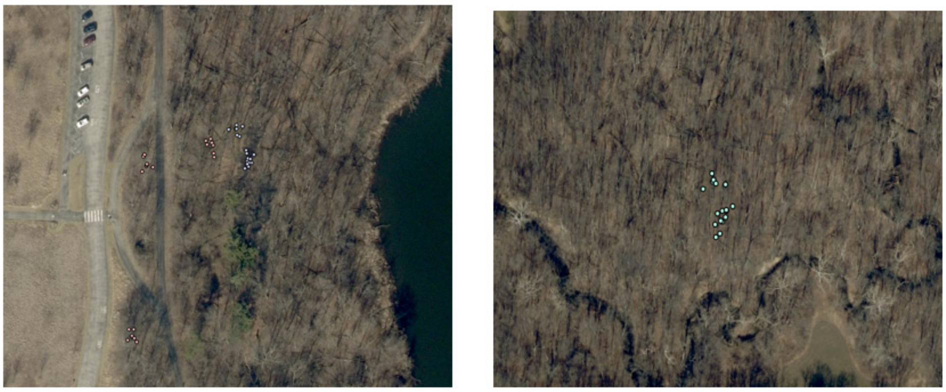

Figure 1. Study Sites for CBDS_Small Data Collection: Celery Bog Nature Center (**left**) and Richard G. Lugar Forestry Farm (**right**).

2.2. Image Collection

High-resolution bark images were captured using an iPhone 14 Pro equipped with LiDAR capabilities, which enhances depth perception and image quality, critical for capturing fine bark textures and patterns. The LiDAR sensor improves focus and detail in complex natural environments, ensuring that images accurately represent bark characteristics under varying conditions. Diameter at breast height (DBH) measurements were obtained using a Spencer logger's tape, a standard forestry tool, with values rounded to the nearest inch to maintain consistency. To investigate variables contributing to AI model misclassification, we standardized tree size and age across the three target species—northern red oak, hackberry, and bitternut hickory—as illustrated in Figure 2. Only trees with a DBH of 16–18 inches were included, as this range corresponds to mature trees with well-developed bark textures, minimizing variations due to ontogenetic differences. This standardization reduces confounding factors such as bark immaturity or excessive roughness found in older trees, ensuring that observed differences in classification accuracy are attributable to the investigated variables (time of day, moisture level, and cardinal direction) rather than tree morphology. Field protocols were designed to ensure data reliability and reproducibility for future studies.

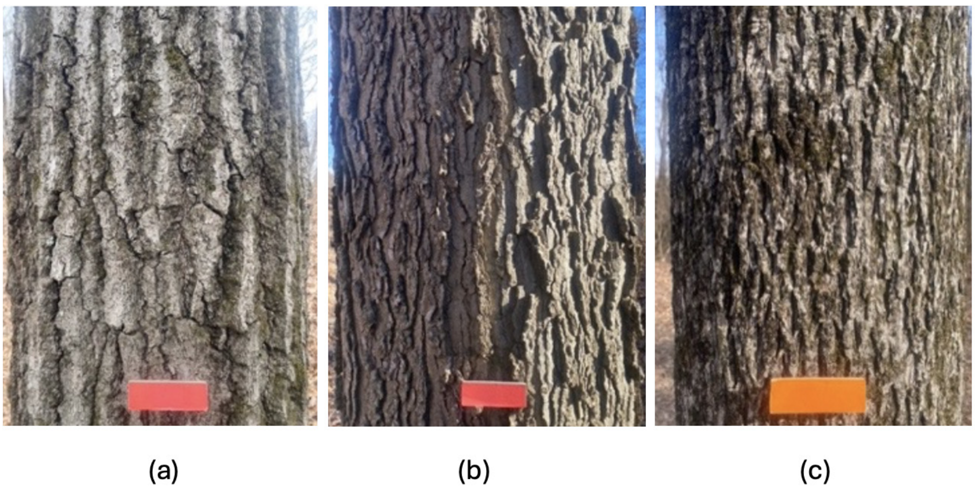

Figure 2. Bark Images of (**a**) northern red oak, (**b**) hackberry, and (**c**) bitternut hickory.

2.3. Data Description

To investigate the factors influencing AI model performance, we examined three variables: time of day (which affects lighting conditions), bark moisture level (wet or dry), and the cardinal direction of image capture (North, East, South, or West). These variables were selected based on their potential to alter bark appearance, as lighting, moisture, and directional shadows can obscure or enhance diagnostic features. CBDS_Small focuses on three species based on their data availability and prior model performance [9]. Each species—northern red oak, (91.28% accuracy), hackberry (75.53% accuracy), and bitternut hickory (63.38% accuracy)—had at least 125 data points, with each data point comprising four images (one per cardinal direction), yielding a minimum of 500 images per species [9]. This selection strategy enabled us to assess model robustness across a spectrum of classification accuracies, ranging from high to low performers, and provided insights into differential error sources. Field data collection leveraged the ArcGIS Field Maps application, which facilitated offline data capture using the iPhone 14 Pro, ensuring operational efficiency in remote forest settings. Images and metadata, including GPS coordinates, timestamp, date, and camera settings, were stored offline and uploaded upon re-establishing an internet connection, maintaining data integrity. To capture lighting variability, images were taken at three time intervals: morning (07:00–10:00), afternoon (12:00–15:00), and evening (17:00–20:00), corresponding to distinct solar angles and light intensities. Bark moisture was assessed by collecting images on rainy, overcast days (wet bark) and dry, sunny days (dry bark), reflecting common environmental conditions. Our new CBDS_Small dataset comprises 252 images, with 96 images of northern red oak, 84 images of hackberry, and 72 images of bitternut hickory. For each tree, four images were captured in a counterclockwise sequence (North, West, South, East) to evaluate directional effects. To ensure consistency, only three trees per species were sampled, yielding a minimum of 72 images across nine trees. These controls standardized bark characteristics, minimizing confounding variables and enhancing the reliability of findings.

2.4. Bark Image Classification

Prior research [9] demonstrated that Convolutional Neural Networks (CNNs) are effective for bark image classification. We evaluated three models: EfficientNet-B3 [10], ResNet-50 [11], and MobileNet-V3-small [12]. For this paper, we focus solely on EfficientNet-B3, which achieved the highest overall accuracy of 83.21% in our previous work [9]. Its balance of computational efficiency and high performance makes it ideal for analyzing how environmental factors influence classification accuracy.

We compared the experimental design of CBDS_Small with that of the Central-Bark Dataset from our previous work [9]. While CBDS encompassed 25 species across 19,147 images from 4697 trees, CBDS_Small is deliberately smaller, with 252 images from 9 trees of 3 species. This focused approach isolates and analyzes the impact of environmental variables—time of day, bark moisture, and cardinal direction—on classification accuracy, allowing us to attribute performance differences to these specific factors rather than dataset scale or model architecture.

The model was trained using the Adam optimizer [13] with a learning rate of 0.01 and a cross-entropy loss function, standard choices for optimizing deep learning models in image classification tasks. To enhance robustness and mitigate overfitting, we applied data augmentation techniques, including random image rotation, horizontal and vertical flipping, and grayscale transformations, which simulate natural variations in image capture. All models were trained on 224×224-pixel input images with a mini-batch size of 32, a configuration optimized for computational efficiency and model convergence. The validation strategy, stratified five-fold cross-validation with tree-level splitting, remains consistent with our previous work. During testing, test images were center-cropped and rescaled to the required dimensions to evaluate the dataset's baseline performance under standardized conditions.

3. Results and Discussion

Analysis of the CBDS_Small dataset revealed classification accuracies that both aligned with and diverged from trends observed in our prior research using the larger CentralBark dataset [9]. As presented in Table 1, hackberry and northern red oak exhibited a reversal in relative performance compared to earlier studies. Specifically, hackberry achieved a classification accuracy of 90.00%, outperforming northern red oak at 86.46% by a margin of 3.54%. This shift is notable, given that northern red oak previously demonstrated higher accuracy (91.28%) in the CentralBark dataset. However, the smaller sample size of the current dataset—comprising 96 images for northern red oak, 84 for hackberry, and 72 for bitternut hickory—warrants cautious interpretation. The dataset involved repeated imaging of the same trees under varying light conditions, moisture levels, and cardinal directions, potentially amplifying specific environmental influences not fully captured in the larger dataset. Consistent with expectations, bitternut hickory exhibited the lowest classification accuracy at 26.76%, aligning with its prior performance (63.38%) and underscoring persistent challenges in accurately classifying this species. The low accuracy for bitternut hickory may stem from its subtle bark features, which are less visually distinct than those of hackberry or northern red oak, particularly under variable conditions. These findings suggest that while hackberry's distinctive features may confer an advantage in smaller, controlled datasets, scaling up data collection and diversifying environmental conditions are critical to stabilizing model performance across species.

Table 1. Raw classification accuracy for the CBDS_Small vs. CentralBark using the EfficientNEt-b3 model.

Species	CBDS_Small Accuracy (%)	#	CentralBark Accuracy (%)	#
Northern Red Oak	86.46 (3.30)	96	91.28	1158
Hackberry	90.00 (2.88)	84	75.53	846
Bitternut Hickory	26.76 (4.73)	72	63.38	609

Further analysis examined the influence of three environmental variables—cardinal direction of image capture, bark moisture condition, and time of day—on classification accuracy. Table 2 shows that no consistent pattern emerged to suggest that cardinal direction significantly impacted model performance. The maximum observed difference in accuracy was 4.72%, with east-facing images yielding the highest accuracy, 88.42%, and west-facing images the lowest, 83.70%. north- and south-facing images had accuracies of 84.61% and 85.95%, respectively. These results align with our hypothesis that directional effects, particularly those tied to sunrise (east) and sunset (west), may introduce variability due to differences in lighting and shadow patterns. However, the modest variation suggests that cardinal direction is a less dominant factor than anticipated, possibly because the EfficientNet-B3 model [10] is robust to subtle lighting differences caused by directional orientation. This finding has practical implications for field data collection, suggesting that strict control of cardinal direction may not be necessary, thereby allowing for greater flexibility in image capture protocols. Nonetheless, the slight advantage of east-facing images may warrant further investigation into whether morning light enhances bark feature visibility, particularly for species with complex textures.

Table 2. Model performance by cardinal direction across all species.

Direction	Accuracy (%)
North	84.61 (2.38)
West	83.70 (2.49)
South	85.95 (2.47)
East	88.42 (2.15)

Analysis of bark moisture conditions revealed a pronounced impact on classification accuracy, as shown in Table 3. Images captured under dry conditions yielded an accuracy of 89.32%, surpassing wet conditions by 8.19% (81.13% accuracy). This disparity was anticipated for the selected species—northern red oak, hackberry, and bitternut hickory—which exhibit slate-gray bark when dry but darken significantly when wet, altering their visual appearance. For northern red oak, the characteristic "ski track" furrows [14] transitioning from slate gray to off-white become less distinct under wet conditions, potentially confusing the model. Similarly, hackberry's wart-like protuberances [14] a defining feature, may appear subdued when wet, reducing contrast. Bitternut hickory, with its tightly packed bark and narrow slits, is particularly susceptible to misclassification when wet, as moisture masks its subtle peeling texture [15].

Table 3. Impact of bark hydration on prediction accuracy across all species.

Moisture Condition	Accuracy (%)	#
Dry	74.86 (3.54)	140
Wet	66.67 (4.05)	108

The classification accuracies for northern red oak, hackberry, and bitternut hickory across morning (07:00–10:00), afternoon (12:00–15:00), and evening (17:00–20:00), as shown in Table 4, reveal the impact of lighting conditions on the EfficientNet-B3 model's performance in bark-based tree identification. Northern red oak achieved the highest accuracies in morning (91.67%) and evening (90.00%) but dropped to 80.80% in the afternoon, likely due to harsh midday light creating high-contrast shadows that obscure its deep furrows. Hackberry exhibited a progressive increase, from 85.00% in the morning to 95.56% in the evening, where low-angle light enhanced its bumpy protuberances, supported by a larger evening sample (45 images vs. 30 for morning/afternoon). Bitternut hickory consistently performed poorly (20.83–33.33%), with its faint bark slits and peeling challenging the model across all conditions, exacerbated by a smaller evening sample (25 images).

Table 4. Classification accuracy by time of day.

Time	Species	Accuracy (%)	#
Morning	Northern red oak	91.67 (5.02)	30
	Hackberry	85.00 (6.48)	30
	Bitternut hickory	20.83 (7.37)	30
Afternoon	Northern red oak	80.80 (6.63)	30
	Hackberry	86.67 (6.17)	30
	Bitternut hickory	33.33 (8.56)	30
Evening	Northern red oak	90.00 (5.45)	30
	Hackberry	95.56 (3.04)	45
	Bitternut hickory	26.00 (8.75)	25

These results align with prior findings, where bark moisture significantly reduced accuracy by 8.19% in wet conditions (Table 3), likely interacting with lighting effects (e.g., wet bark in afternoon light worsening northern red oak's performance). Cardinal direction had minimal impact (4.72% maximum difference, Table 2), emphasizing time of day as a more critical variable. The species' morphological differences—northern red oak's prominent furrows, hackberry's distinctive protuberances, and bitternut hickory's fine features—explain their varying sensitivities to lighting, with hackberry's robustness contrasting with bitternut hickory's persistent challenges.

The findings underscore the need for robust models to handle lighting variations in AI-based tree identification. Augmenting the CentralBark dataset [9] with diverse lighting conditions, particularly afternoon images for northern red oak and varied conditions for bitternut hickory, is essential [3]. Techniques such as illumination normalization or attention mechanisms can enhance feature detection, while species-specific strategies (e.g., oversampling for bitternut hickory) address morphological challenges. These improvements are crucial for practical applications, such as UAV-based monitoring, which supports precision forestry and conservation in dynamic forest environments.

The Chi-Square test results in Table 5 evaluate the association between time of day (morning, afternoon, evening) and classification outcomes (correct or incorrect) for hackberry, northern red oak, and bitternut hickory using the EfficientNet-B3 model for AI-based tree bark identification. Hackberry (χ^2 = 10.9877, p = 0.0041) and northern red oak (χ^2 = 7.6633, p = 0.0217) show significant associations ($p < 0.05$), confirming that lighting conditions significantly influence their classification accuracy. Hackberry's accuracy peaks at 95.56% in the evening, likely due to low-angle light enhancing its nodular appearance, while northern red oak's accuracy drops to 80.80% in the afternoon, where harsh light obscures its grooved furrow pattern, compared to 91.67% in the morning and 90.00% in the evening. Bitternut hickory's non-significant result ((χ^2 = 4.8251), (p = 0.0896)) aligns with its consistently low accuracies (20.83–33.33%), reflecting challenges in detecting its subtle bark slits across all lighting conditions, compounded by a smaller evening sample (25 images vs. 30 for others).

Table 5. Chi-square Test: Binary Classification among different time/light conditions.

Species	Chi-Square	*p*-Value
Hackberry	10.99	<0.05
Northern red oak	7.66	0.02
Bitternut hickory	4.83	0.09

These findings complement prior results found in Warner et al. (2024) [9], where bark moisture reduced accuracy by 8.19% in wet conditions, likely exacerbating lighting effects (e.g., wet bark in afternoon light for northern red oak), and cardinal direction had minimal impact (4.72% difference). The significant results for hackberry and northern red oak highlight their sensitivity to lighting due to distinct morphological features, while bitternut hickory's non-significant result highlights its morphological challenges. The study suggests augmenting the CentralBark dataset [9] with more afternoon images for northern red oak and diverse conditions for bitternut hickory, alongside preprocessing techniques like illumination normalization [2]. Hackberry's robustness suggests less augmentation for distinct species, while bitternut hickory needs species-specific strategies.

Limitations

We can confirm that no data leakage occurred in this study. Our CBDS_Small dataset, comprised of 252 images, was used exclusively for testing and not included in the training of the EfficientNet-B3 model. Furthermore, both Centralbark and CBDS_Small, the training is split by trees and not by images.

The moisture-induced color shift highlights a critical limitation in current deep learning models, which rely heavily on color and texture cues [3]. Addressing this challenge requires targeted augmentation of training datasets with wet bark images and potential preprocessing techniques, such as color normalization, to mitigate the impact of moisture on feature detection. These findings underscore the need for robust models capable of generalizing across environmental conditions encountered in real-world forestry applications.

4. Conclusions

The novelty of this paper is the evaluation of the EfficientNet-B3 model's robustness in AI-based bark classification using CBDS_Small, focusing on environmental impacts–time of day, bark moisture, and cardinal direction on northern red oak, hackberry, and bitternut hickory classification. The analysis of a CBDS_Small dataset revealed that hackberry outperformed northern red oak (90.00% vs. 86.46% accuracy), reversing prior trends from the CentralBark dataset [9], while bitternut hickory consistently exhibited low accuracy (26.76%), aligning with its prior performance (63.38%). These results were influenced by the smaller sample size and repeated imaging under varied conditions. Furthermore, the observed reversal in trends for hackberry vs. northern red oak is likely to stem from its distinct physical characteristics, which facilitate identification across all life stages. Hackberry's characteristic wart-like protrusions are not as prominent on young trees, unlike red oak, where diagnostic features like "ski tracks" show pretty early in the tree's life cycle. At the 10-inch DBH threshold used in Warner et al., 2024 northern red oak is more readily distinguishable than hackberry [9]. This difference becomes more pronounced in our study, which targets a 16–18-inch DBH range, where hackberry's prominent features enhance its recognizability in our smaller dataset. and underscore the interplay of species morphology and environmental factors in model performance.

Bark moisture condition emerged as a significant factor, with dry conditions yielding 8.19% higher accuracy than wet conditions (89.32% vs. 81.13%), as wet bark darkens the normal appearance like northern red oak's "ski tracks", hackberry's wart-like texture, and bitternut hickory's imperceptible bark characteristics. Time of day also significantly affected accuracy, with Chi-Square tests confirming strong associations for hackberry (χ^2 = 10.99, p = <0.05) and northern red oak (χ^2 = 7.66, p = 0.02), driven by evening (95.56% for hackberry) and morning (91.67% for northern red oak) light enhancing feature visibility, while afternoon's harsh light reduced northern red oak's accuracy (80.80%). Bitternut hickory's non-significant result (χ^2 = 4.83, p = 0.09) reflects its morphological challenges, as its subtle features remain difficult to classify across all lighting conditions. Cardinal direction had minimal impact (4.72% maximum difference), suggesting that lighting intensity and angle are more critical than directional shadows.

These findings highlight the need for robust deep learning models to address environmental variability in AI-based tree identification. Targeted augmentation of the CentralBark dataset with wet bark and afternoon images, particularly for northern red oak, and diverse conditions for bitternut hickory, is essential to improve model generalization. Preprocessing techniques, such as illumination normalization and attention mechanisms, could enhance feature detection under varying light and moisture conditions [2]. Species-specific strategies, including oversampling or transfer learning for bitternut hickory, are crucial to overcome morphological challenges. These improvements are vital for practical applications like UAV-based monitoring [16], enabling reliable automated species identification in dynamic forest environments.

5. Future Work

Despite limitations, such as potential non-independence from repeated tree imaging and varying sample sizes, this study advances the development of AI tools for digital forestry. By addressing lighting and moisture-related errors and tailoring approaches to species with subtle features, the research supports precision forest management, biodiversity monitoring, and conservation efforts in the face of ecological challenges like climate change and invasive species. Future work should explore and not be limited to the CentralBark dataset. Using other well-known datasets could reveal the ability to pinpoint specific time-of-day effects and develop advanced modeling techniques to enhance accuracy for challenging species, further bridging the gap between human expertise and automated tree identification.

Author Contributions: Conceptualization, R.G. and C.W.; methodology, C.W. and F.W.; software, F.W.; validation, C.W. and F.W.; formal analysis, F.W.; investigation, C.W. and F.W.; resources, C.W.; data curation, F.W.; writing—original draft preparation, C.W. and F.W.; writing—review and editing, R.G., B.B. and S.F.; visualization, F.W.; supervision, R.G. and S.F.; project administration, R.G.; funding acquisition, R.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work is partially supported by the PERSEUS project, award # 2023-68012-38992 under USDA NIFA. The views and conclusions contained herein are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of NIFA or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for governmental purposes, notwithstanding any copyright annotation therein. This work was supported by NSF grants 2417510 and 2412928. This work was also supported by USDA NIFA grants 1032382 and 1032672.

Data Availability Statement: The authors of this paper will release 1 image for each species found in the CentralBark Database. The remainder of the data will be withheld for the continuation of research at Purdue University's Institute for Digital Forestry.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Fiel, S.; Sablatnig, R. Tree Species Dataset consisting of Images of the Bark, Leaves or Needles [Data set]. *Zenodo* **2010**. [CrossRef]
2. Lecun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. Gradient-based learning applied to document recognition. *Proc. IEEE* **1998**, *86*, 2278–2324. [CrossRef]
3. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016; Available online: http://www.deeplearningbook.org (accessed on 5 May 2025).
4. Carpentier, M.; Giguere, P.; Gaudreault, J. Tree Species Identification from Bark Images Using Convolutional Neural Networks. In Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Madrid, Spain, 1–5 October 2018; pp. 1075–1081. [CrossRef]
5. Cui, Z.; Li, X.; Li, T.; Li, M. Improvement and Assessment of Convolutional Neural Network for Tree Species Identification Based on Bark Characteristics. *Forests* **2023**, *14*, 1292. [CrossRef]
6. Lakmann, R. *Barktex Benchmark Database of Color Textured Images*; Koblenz-Landau University: Mainz, Germany, 1998.
7. Ratajczak, R.; Bertrand, S.; Crispim-Junior, C.; Tougne, L. Efficient bark recognition in the wild. In Proceedings of the International Conference on Computer Vision Theory and Applications (VISAPP2019), Prague, Czech Republic, 25–27 February 2019.
8. Misra, D.; Crispim-Junior, C.; Tougne, L. Patch-Based CNN Evaluation for Bark Classification. In Proceedings of the Computer Vision—ECCV 2020 Workshops, Glasgow, UK, 23–28 August 2020; pp. 197–212. [CrossRef]
9. Warner, C.; Wu, F.; Gazo, R.; Benes, B.; Kong, N.; Fei, S. CentralBark Image Dataset and Tree Species Classification Using Deep Learning. *Algorithms* **2024**, *17*, 179. [CrossRef]
10. Tan, M.; Le, Q.V. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. *arXiv* **2019**. [CrossRef]
11. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.
12. Howard, A.; Sandler, M.; Chu, G.; Chen, L.-C.; Chen, B.; Tan, M.; Wang, W.; Zhu, Y.; Pang, R.; Vasudevan, V.; et al. Searching for MobileNetV3. *arXiv* **2019**, arXiv:1905.02244.

13. Kingma, D.P.; Ba, J. Adam: A Method for Stochastic Optimization. *arXiv* **2014**, arXiv:1412.6980. [CrossRef]
14. Weeks, S.S.; Weeks, H.P.; Parker, G.R. *Native Trees of the Midwest: Identification, Wildlife Values, and Land-scaping Use*, 2nd ed.; Purdue University Press: West Lafayette, IN, USA, 2010.
15. Wojtech, M.; Wessels, T. *Bark: A Field Guide to Trees of the Northeast*; Brandeis University Press: Waltham, MA, USA, 2011.
16. Torresan, C.; Berton, A.; Carotenuto, F.; Di Gennaro, S.; Gioli, B.; Matese, A.; Miglietta, F.; Vagnoli, C.; Zaldei, A.; Wallace, L. Forestry applications of UAVs in Europe: A review. *Int. J. Remote Sens.* **2016**, *38*, 1–21. [CrossRef]