

Overcoming Structural and Environmental Challenges in Identifying Brazilian Savanna Tree Species Using Deep Learning

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Abstract

The Brazilian Cerrado, a global biodiversity hotspot, faces persistent challenges in species identification due to the limitations of phenology-dependent methods in its seasonally dynamic landscapes. This study evaluates the performance of convolutional neural networks (CNNs) for bark-image-based classification of three ecologically prominent tree species: *Apuleia leiocarpa*, *Astronium fraxinifolium*, and *Vochysia haenkeana*. We compiled 1,515 bark images from individual trees (DBH $\geq$ 25 cm) during the 2023–2024 rainy seasons and applied data augmentation and normalization. Using the MobileNetV2 architecture, we trained and validated the model with metrics including Accuracy, Precision, Recall, F1-score, Confusion Matrix, ROC/AUC curves, and t-SNE projections. The model achieved an overall accuracy of 90.52%. Bark morphological complexity strongly influenced classification: *V. haenkeana*, with distinct patterns, showed the highest performance (Precision 1.00, Recall 0.94), while *A. fraxinifolium* and *A. leiocarpa*, which share more convergent bark traits, exhibited higher misclassification rates (22.54%). These results demonstrate how interspecific bark variability affects CNN discrimination and confirm that intrinsic bark heterogeneity (e.g., rhytidome texture, rugosity, color patterns, scars) and environmental variation increase classification difficulty. Our findings highlight the potential of bark-based deep learning models as phenology-independent tools for large-scale forest inventories and biodiversity monitoring in complex ecosystems. A key limitation is the dataset's restriction to a single seasonal period, underscoring the need for broader temporal sampling. This study reinforces the role of deep learning in delivering scalable and accurate solutions for ecological research and conservation in understudied biodiversity hotspots.

Introduction

South American savannas represent a significant portion of global savanna coverage, spanning over 2.29 million square kilometers and distinguishing themselves as the wettest and most biodiverse spectrum globally (Lira-Martins et al. 2022; Rocha and Pinto 2021; Schwaida et al. 2023). The Brazilian Cerrado, a globally recognized biodiversity hotspot, harbors an extraordinary diversity of endemic species essential for ecosystem functioning and resilience (Lira-Martins et al. 2022; Rabeling et al. 2019). Its structural and compositional complexity creates a mosaic of ecological niches, supporting exceptionally high levels of functional diversity (Lira-Martins et al. 2022; Rocha and Pinto 2021; Schwaida et al. 2023). Yet, despite its ecological prominence, the Cerrado remains critically understudied, posing substantial challenges for accurate species identification and evidence-based conservation planning (Colli et al. 2020; Mustin et al. 2017; Silveira et al. 2025). Indeed, the comprehensive understanding of biodiversity is frequently hampered by “knowledge shortfalls”, where crucial research questions remain unanswered due to data deficiencies (Hortal et al. 2015). Such deficiencies are often exacerbated by the fact that traditional approaches, such as classical taxonomy and botanical field surveys, though foundational, face inherent challenges in providing comprehensive and efficient large-scale identification (Arora et al. 2025; Rzanny et al. 2019). These challenges arise especially due to the psychophysiological complexity of seasonal forest formations and logistical constraints that hinder professional access to remote areas (Meyer et al. 2016).

In response to these substantial identification challenges that hinder effective biodiversity management, novel technological solutions are rapidly transforming ecological assessment and monitoring. Among these, convolutional neural networks (CNN's) have emerged as remarkably powerful tools for large-scale species monitoring (Li et al. 2020; Zhang et al. 2024). Their unparalleled ability to analyze complex spatial, temporal, and spectral data with high precision stems from their design as deep learning models, capable of automatically identifying intricate hierarchical patterns - including edges, textures, and shapes - thereby circumventing the need for extensive manual feature engineering (Aggarwal 2018; Warner et al. 2024a). This inherent proficiency has driven their widespread adoption in diverse ecological applications, ranging from accurate species identification and habitat mapping to critical environmental monitoring, such as deforestation detection and assessment (Kim et al. 2022). Furthermore, CNN-based models have demonstrated significant potential for forest inventories, enabling rapid and accurate classification of plant species from remote sensing data and successfully integrated into drones and scanning systems for detailed insights into inaccessible forested areas (Nooralishahi et al. 2021; Wu et al. 2021).

Despite the well-established efficacy of CNN's in various Classification tasks, a significant research gap persists regarding their specific application for native Cerrado tree species. Identifying these species through bark morphology offers a non – destructive approach, especially valuable when key phenological traits are seasonally inconspicuous (Kim et al. 2022). This is crucial, as botanical surveys frequently encounter abundant sterile vegetative material, and species identification in the Cerrado is further complicated by intraspecific variation across diverse habitats (e.g., forests, open fields, various soil types) (Blaanco et al. 2016; Fekri-Ershad 2020). Furthermore, bark offers high consistency throughout seasons and easy accessibility, even in high crown conditions (Rosell et al. 2014). However, its full potential for automated identification remains critically underexplored for species within semideciduous seasonal forest formations (Fekri-Ershad 2020). This gap is critical given the unique complexities of this biome and the urgent need for enhanced conservation tools. While expert botanists can often distinguish these species based on a combination of traits, complementary technological tools, including AI-driven systems, are increasingly essential to support field identification efforts (Caccianiga et al. 2021; Enríquez-de-Salamanca). Such tools can provide rapid, large-scale assessment, crucial for enhancing existing botanical knowledge and aiding conservation amidst rapid savanna destruction and climate change. This aligns with the broader development of interactive identification keys and comprehensive digital databases.

This inherent difficulty in identification stems from subtle morphological variations, similar bark coloration, and shared intrinsic bark features (e.g., rhytidome texture, rugosity, color patterns, and scars) among co-occurring species (Gama et al. 2025; Surendran et al. 2025). This challenge is especially exacerbated during dry seasons and fires, when key phenological traits are less available for accurate diagnosis (Lira-Martins et al. 2022; Rabeling et al. 2019). Such challenges make specialized knowledge and precise identification tools limiting students in early stages of training and non-specialized individuals. For instance, environmental plasticity leads to confusion even for seemingly distinct species: *Vochysia haenkeana*, despite its marked yellow coloration, is often mistaken for *Albizia niopoides* by

non-specialists. Similarly, *Apuleia leiocarpa* and *Astronium fraxinifolium* present highly similar rhytidome patterns and variable coloration in different environments (e.g., more brownish in closed forest vs. typical ashen/dark yellow in open environments), leading to frequent misidentification. Furthermore, these three species – *V. haenkeana*, *A. leiocarpa*, and *A. fraxinifolium* - can be confused with each other by the local community, as their bark tends to become more yellowish and subtly smooth depending on the time of year and climatic conditions, intensifying the ambiguity in visual identification.

This ambiguity directly impacts the sustainable use of the Cerrado rich flora. Many species, particularly those in semideciduous seasonal forest formations, possess high economic potential (e.g., valuable timber, edible fruits, medicinal properties, non-timber forest products) (Berte et al. 2024; Silva-Pereira et al. 2011). However, their sustainable exploitation and valorization are severely hindered by this ongoing identification ambiguity, preventing adequate economic valuation and limiting community engagement in sustainable forest management (Souza et al. 2016a). Consequently, this contributes to the undervaluation and displacement of native resources by expanding agricultural frontiers, further exacerbating biodiversity loss (Rouhan and Gaudeul 2014). Given the proven social acceptance of CNN's among farmers and increasing initiatives for savanna plants thorough these networks are highly promising (Hajjaji et al. 2025; Nogueira et al. 2019). This allows producers to identify valuable species without confusion, fostering sustainable economic development and empowering local communities within the Cerrado.

To directly address this pressing research and practical challenge, this study investigates the applicability of advanced deep learning techniques. Specifically, we evaluate the MobileNetV2 convolutional neural network for classification of three ecologically prominent Cerrado tree species - *Apuleia leiocarpa* (Fabaceae), *Astronium fraxinifolium* (Anacardiaceae), and *Vochysia haenkeana* (Vochysiaceae) - based solely on bark images. These species were selected for their ecological significance, widespread occurrence, and the morphological complexity of their bark surfaces, which present a nuanced and realistic challenge for automated recognition systems, as highlighted by the field identification difficulties and their economic/ecological value.

Our research is guided by two central questions, which also represent key methodological challenges in this context: Firstly, we aim to understand how the inherent morphological complexity of bark influences CNN classification accuracy, particularly when differentiating between species exhibiting simpler versus more intricate patterns. Secondly, we investigate how the model's performance is influenced by natural variability of intrinsic bark characteristics. This includes assessing the impact of features integral to itself – such as rhytidome texture and rugosity, color patterns, and the presence of scars – which can act as confounding variables for the classifier. By systematically exploring these questions, this study aims to promote CNN-based species identification methodologies and advance the application of deep learning in biodiversity conservation within conservation within complex ecosystems. Our findings will not only underscore the promising role of artificial intelligence in ecological research but also transparently delineate the practical limitations and highlight crucial future directions for developing

highly accurate and robust CNN-based identification systems tailored for challenging ecological contexts.

Methods

Field Study and Data Collection

This study employed a dataset specifically acquired to investigate bark texture patterns of tree species in the Brazilian savanna (Cerrado). A total of 1,515 images were systematically collected, evenly distributed among three native tree species within this biome: *Apuleia leiocarpa* (Vogel) J.F. Macbr. (Fabaceae), *Astronium fraxinifolium* Schott (Anacardiaceae), and *Vochysia haenkeana* Mart. (Vochysiaceae). Crucially, each species contributed 505 unique images, with each image representing a distinct individual tree, all with a Diameter at Breast Height (DBH) equal to or greater than 25 cm. Images were captured during the rainy seasons of 2023 and 2024, in mesophytic forests located in southern Goiás State, Brazil, specifically the municipalities of Piracanjuba (17°18'30.42"S, 49°1'44.37"W) and Abadia de Goiás (16°45'25.44"S, 49°25'35.12"W). Representative examples of the bark morphology for each species are presented in Fig. 1, including both general trunks. A map illustrating the spatial distribution of the sampled individuals is provided in Fig. 2. The selection of these species was previously justified in the Introduction based on their ecological significance, widespread occurrence, and the morphological complexities of their bark surfaces, which present a nuanced challenge for automated identification systems. This selection strategy was integral to our experimental design, allowing us to evaluate the model's performance across a spectrum of bark morphological distinctiveness, from more uniform to subtly convergent patterns.

For image acquisition, two types of equipment were utilized to ensure diversity and quality in the records: a Nikon D90 camera (equipped with an 18–105 mm lens, 4288 x 2848 pixels resolution), and the integrated camera of a Samsung Galaxy A71 smartphone (4000 x 3000 pixels resolution). All images were stored in JPEG format. Acknowledging the inherent variability of natural light incidence and the dynamic influence of canopy openness in understory environments, efforts were made to standardize image capture. During collection, the imaging device was consistently positioned perpendicular to the tree trunk, at distance ranging from 20 cm to 40 cm, depending on the conditions found in the field (Gama et al. 2025). Image capture was performed under natural lighting conditions, specifically between 9:00 AM and 3:00 PM, to mitigate extreme variations in light intensity and shadow effects. The residual variations in lighting and other environmental factors inherent to field data were specifically addressed during the dataset preprocessing through robust data augmentation techniques (as detailed in Section Dataset Preparation and Preprocessing), designed to enhance the model's resilience to diverse real-world conditions.

Machine Learning Pipeline Overview

The overall methodology for bark image classification, encompassing data preparation, model training, and evaluation, is schematically presented in Fig. 3. This pipeline was designed to rigorously test our research questions regarding the influence of bark morphology and superficial elements on CNN classification accuracy. The following subsections detail each component of this pipeline.

Dataset Preparation and Preprocessing

Upon collection, all images were initially in JPEG format and organized using the Hierarchical Dataset Organization (Xu and Goodacre 2018). To optimize feature extraction and computational efficiency for CNN training, and to enhance the detection of local texture patterns, the original high-resolution bark images were segmented into multiple smaller sub-images, or patches (Altal et al. 2025). From each original image, 60 random patches of 256 x 256 pixels were extracted, a number considered adequate according to previous studies utilizing between 9 and 80 patches (Elgamily et al. 2025; Misra et al. 2020). This resulted in a total dataset of 90,900 patches for analysis. This patch-based approach is particularly beneficial for training convolutional neural networks as it increases dataset variability and focuses the model on fine-grained textural details. This patch-based approach is particularly advantageous for training convolutional neural networks, as it increases dataset variability and optimizes the model's focus on fine-grained textural details (Baihaqi et al. 2025).

The dataset was systematically divided into stratified training, validation, and test sets to ensure robust model development and unbiased evaluation (Liu et al. 2025). For each species, 85% of the images were allocated for model training and validation, while the remaining 15% were exclusively reserved for the test set (Cicero et al. 2017; Shah et al. 2020). This partitioning ensures that the model's generalization performance is evaluated on unseen data, mitigating potential *overfitting* (Altal et al. 2025).

To further enhance the model's ability to generalize across diverse real-world lighting and orientation conditions, and to effectively prevent overfitting, data augmentation techniques were extensively applied to the training set (Shorten et al. 2021). These techniques included randomized adjustments such as rotation ($\pm 20^\circ$), zoom ($\pm 20\%$), horizontal flipping, and brightness modifications ($\pm 15\%$). Prior to model training, all images underwent a crucial normalization process (Kumar et al. 2024), where pixel values were rescaled to the [0, 1] range. This preprocessing step ensured data uniformity, mitigated potential illumination variances, and guaranteed compatibility with the MobileNetV2 model's input requirements (Indraswari et al. 2022).

Machine Learning

The MobileNetV2 architecture, a highly efficient convolutional neural network, was selected for its proven capability in detecting relevant features in images, making it suitable for deployment on mobile and edge devices (Gulzar 2023). This architecture, configured with *transfer learning* techniques, leverages a model pre-trained on the extensive ImageNet database (Akay et al. 2021). This pre-training provides an initial set

of robust recognition features (Al-Gaashani et al. 2025), such as edges, textures, and shapes, which are then fine-tuned to the specific characteristics of our bark image dataset.

Hyperparameter optimization was a critical step to enhance the model's robustness and reliability (Kumaresan et al. 2021). Beyond standard parameters like learning rate, number of epochs, and batch size, the optimization process aimed to fine-tune the model's capacity to automatically extract and differentiate salient morphological patterns from bark images. This approach enabled the model to effectively adapt to and discern subtle morphological specificities and potential visual noise inherent in our dataset, directly addressing aspects related to our research questions concerning bark complexity and superficial elements (Altal et al. 2025). Qualitative characteristics of bark morphology, including external coloration, texture, thickness, shedding pattern, color change with shedding, and the presence of superficial elements (e.g., lichens, bryophytes, scars), were visually assessed during dataset preparation (Fig. 4). This visual assessment provided crucial insights for experimental design and aided in diagnosing model performance and classification challenges.

Model Evaluation and Statistical Analysis

Prior to model evaluation, and to investigate potential spatial autocorrelation that could affect subsequent analyses, a Moran's I analysis was conducted for key intrinsic bark characteristics, including rhytidome texture, bark dimension (length, width, thickness, and weight), rugosity, color patterns, and scars. This analysis, performed using the Geoda software v.1.8.10 (Anselin et al. 2005), revealed no significant spatial autocorrelation for these variables, suggesting their spatial independence (Moran et al. 2021).

The MobileNetV2 classification model's performance was rigorously evaluated on an independent test set using standard metrics, providing insights crucial for addressing our research questions. These metrics included Accuracy (ACC), representing overall correct predictions; Precision (P), measuring the quality of positive predictions; Recall (R), quantifying the model's sensitivity to identify all positive instances; and the F1-score (F1), the harmonic mean of Precision and Recall, indicating a balanced performance. Their calculations are defined as:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

$$P = \frac{TP}{TP + FN}$$

$$R = \frac{TP}{TP + FP}$$

$$F1 = 2 * \frac{P * R}{P + R}$$

Where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively (Leiva-Bianchi et al. 2025; Yang et al. 2025a).

The confusion matrix was employed to systematically visualize classification performance across species. This matrix was critical for assessing the model's ability to distinguish species with similar bark characteristics (Fan 2025; Miftahushudur et al. 2025), particularly *A. fraxinifolium* and *A. leiocarpa*, thereby directly informing our investigation into how morphological complexity influences CNN classification accuracy. It also facilitated the identification of misclassification patterns potentially linked to visual noise from superficial elements, contributing to our understanding of the impact of such confounding features on model performance (Miftahushudur et al. 2025).

For further interpretation of the model's discriminative capabilities, Receiver Operating Characteristic (ROC) curves and their Area Under the Curve (AUC) were generated for each species (Huo and Glickman 2025). Additionally, t-Distributed Stochastic Neighbor Embedding (t-SNE) was applied to visualize high-dimensional feature vectors in two dimensions, revealing data clusters and patterns of similarity or overlap among species in the latent space (Mohammad et al. 2025). These visualizations provided qualitative insights into how the model differentiates, or struggles to differentiate, species based on bark morphology and the impact of visual noise, supporting the interpretation of our research findings.

Plant Material

The three native Cerrado tree species - *Apuleia leiocarpa* (Fabaceae), *Astronium fraxinifolium* (Anacardiaceae), and *Vochysia haenkeana* (Vochysiaceae) - were selected due to their ecological significance, widespread occurrence, and high economic potential in semideciduous seasonal forest formations (Souza et al. 2016b). Their identification presents significant challenges stemming from subtle morphological variations, variable bark coloration (influenced by environment and season), and shared superficial features (e.g., coloration, texture, and scars). This complexity leads to frequent misidentification by non-specialists, with other co-occurring species like *Albizia niopoides* and among themselves (*A. leiocarpa*, *A. fraxinifolium*, and *V. haenkeana*) (Martello et al. 2023). These inherent ambiguities severely hinder the sustainable exploitation and valorization of these valuable resources, ultimately contributing to the undervaluation and displacement of native resources by agricultural expansion (Martello et al. 2023). Consequently, these species serve as ideal test cases for evaluating AI-driven tools in addressing real-world identification bottlenecks in complex and economically vital ecosystems.

Results

The MobileNetV2 model demonstrated strong performance in classifying the three Cerrado tree species from bark images. The model's performance metrics and visual analytics, including the confusion matrix, Receiver Operating Characteristic (ROC) curves, a heatmap of bark characteristics, and t-SNE visualizations, are comprehensively presented in Fig. 5 and Table 1.

Table 1
Classification report of the MobileNetV2 model performance for each tree species, presenting key evaluation metrics and confusion matrix components.

	Precision	Recall	F1-score	TP	FP	FN	AUC
<i>Astronium fraxinifolium</i>	0.96	0.77	0.86	55	2	16	0.96
<i>Apuleia leiocarpa</i>	0.80	1.00	0.89	72	18	0	0.98
<i>Vochysia haenkeana</i>	1.00	0.94	0.97	64	0	4	0.99
Accuracy			0.91				
Macro AVG	0.92	0.91	0.91				
Weighted AVG	0.92	0.91	0.91				
* True Positives (TP); False Positives (FP); False Negatives (FN).							

The confusion matrix analysis (Table 1) revealed an overall prediction accuracy of 90.52%. Consistent with this, the weighted average F1-score was 0.91, indicating a good balance between precision and recall across all species. The highest classification error rate (22.54% of misclassifications, corresponding to 16 False Negatives for *A. fraxinifolium* and 18 False Positives for *A. leiocarpa*) was observed between *A. fraxinifolium* and *A. leiocarpa*. This difficulty is associated with these species sharing common intrinsic bark characteristics such as rhytidome texture, rugosity, color patterns, and scars, whose variability is further compounded by environmental factors like the presence of lichens and bryophytes during the rainy season, which increase visual complexity.

Detailed performance metrics for each species are also presented in Table 1. Conversely, *V. haenkeana* showed superior classification performance, with a low error rate of 5.88%. This species achieved a perfect Precision of 1.00 and a high Recall of 0.94, resulting in an F1-score of 0.97. The discriminative ability for *V. haenkeana* was further supported by a high Area Under the Curve (AUC) value of 0.99. For *A. fraxinifolium* and *A. leiocarpa*, AUC values were also high at 0.96 and 0.98, respectively.

Discussion

The rapid advancements in convolutional neural networks (CNN's) and deep learning techniques have profoundly transformed species identification, notably by enabling the analysis of complex morphological patterns (Kattenborn et al. 2021; Zhang et al. 2022). Historically, primary diagnostic features for plant identification have centered on leaves (Quach et al. 2023), flowers and fruits (Wang et al. 2022). However, recent studies have increasingly highlighted the critical role of bark texture as a robust alternative or complementary tool, particularly in contexts where phenological traits are seasonally absent or unreliable (Bhusnurmath and Doddamani 2023; Kim et al. 2022). This progress is especially pertinent in biodiverse tropical regions like the Cerrado, where high species coexistence and pronounced phenological variations, influenced by environmental factors such as seasonality, climate,

wildfires, and anthropogenic activities, complicate traditional identification efforts (Katsis et al. 2022). Our findings align with this growing recognition, demonstrating the viability of bark morphology as a distinguishing characteristic for species classification in such complex environments.

The findings of this study strongly support our first research question, confirming that species' inherent morphological complexity directly influences CNN classification accuracy. While Fig. 1 indeed illustrates a range of bark morphologies among our selected species, from highly distinct to subtly similar patterns, this was a deliberate and integral aspect of our experimental design, not a fragility. This strategic selection allowed us to rigorously evaluate the model's performance across a spectrum of bark morphological distinctiveness and to gain valuable *insights* into the specific challenges CNN's face when differentiating species based on bark. As hypothesized, *V. haenkeana*, characterized by its more distinct and uniform textural patterns (Fig. 4), achieved superior performance, including a precision rate of 100% and a recall of 94%. This high performance is likely attributed to *V. haenkeana*'s smoother bark, generally lacking marked textures like prominent lenticels or fissures (Fig. 1A-D). Conversely, *A. fraxinifolium* and *A. leiocarpa* exhibited higher misclassification rates due to their significant morphological similarity, particularly in shared features such as lenticels and scars, which present a more intricate and often convergent appearance. Specifically, *A. leiocarpa* bark is typically fissured, rugose, and exfoliates rounded irregular plates, varying in color from brown to gray, whitish, yellowish, or reddish (Fig. 1E-H). Similarly, *A. fraxinifolium* bark is fissured, rugose, and exfoliating in rounded irregular plates, with a color range from brown to gray, whitish, yellowish, or reddish (Fig. 1I-L).

These results underscore the critical role of textural morphology in species differentiation by CNN's, consistent with previous studies (Warner et al. 2025; Warner et al. 2024b). While bark characteristics are known to vary with ontogeny (e.g., thickness and rugosity changing with tree age/size), our sampling approach, which focused on mature individuals with a minimum DBH of 25 cm, aimed to standardize the developmental stage of the sampled trees. However, residual intra-specific variation related to ontogeny could still influence classification performance and represent an inherent complexity of natural datasets.

Our results further confirm the significant influence of common surface elements and environmental variability on the model's classification performance, directly addressing our second research question. The observed greater difficulty in classifying *A. fraxinifolium* and *A. leiocarpa* is notably linked to their shared superficial characteristics, such as lenticels, protuberances, and scars (Fig. 5C). This challenge is exacerbated by the seasonal abundance of epiphytes like lichens and bryophytes during the rainy season, which introduce substantial visual noise and confounding features (Fig. 5C). These elements can obscure subtle bark patterns, effectively blurring the visual distinctions between species, thus hindering CNN's ability to extract precise discriminatory features. This highlights a critical challenge for automated identification systems operating in dynamic natural environments, where visual heterogeneity is inherent and fluctuates with environmental conditions.

In comparison to previous studies, this model demonstrates notable performance, achieving 91% overall accuracy in a highly biodiverse ecosystem like the Cerrado, which surpasses the average accuracy of

89% reported in similar CNN-based tree species identification efforts (Liu et al. 2019). This high performance underscores the practical applicability of our model in supporting large-scale forest inventories and environmental monitoring initiatives. Specifically, the model's capacity to rapidly and accurately assimilate species with simpler textural patterns, as observed for *V. haenkeana*, suggests its immediate utility for initial species screening in extensive projects. Indeed, our findings corroborate the significance potential of AI-based tools to enhance accuracy in forest inventories and support decision-making in tropical forest management (Gama et al. 2025).

Despite the promising performance, this study acknowledges inherent limitations that offer avenues for future research. Firstly, while focusing on mature trees with a standardized DBH minimized ontogenetic variation, comprehensive assessment of temporal patterns and a broader representation of environmental variability (e.g., light conditions, canopy openness across seasons beyond just rainy season) were not exhaustively captured in the current dataset. Secondly, the model's reliance on bark images alone, while advantageous for phenology-independent identification, means it does not integrate other potentially diagnostic features (e.g., leaf, flower, fruit morphology, or phylogenetic context), which could further enhance accuracy, particularly for species with highly convergent bark patterns.

To overcome these limitations and further advance the application of AI in ecological research, future work should prioritize expanding dataset size and diversity to include multiple seasons and broader geographical ranges. Additionally, integrating human expertise for iterative model refinement is crucial. Exploring multimodal deep learning approaches that combine various plant features (e.g., bark, leaf, flower, fruit morphology, or phylogenetic context) could significantly enhance accuracy, applicability, and robustness in diverse and dynamic ecosystems such as the Cerrado (Lapkovskis et al. 2024; Yang et al. 2025b). This is a pertinent investigation, as traditional dichotomous keys for family and genus identification are primarily based on reproductive organs, with limited indications that bark patterns (rhytidoma) could be reliably used. However, the aid of AI, particularly in macro analysis, presents a promising avenue to investigate if structural rhytidome patterns and textural patterns are linked to families and genera, thereby expanding the utility of bark-based identification.

Conclusion

This study demonstrates the strong potential of the MobileNetV2 model for tree species identification in the Brazilian Cerrado using bark images, achieving an overall accuracy of 90.52%. The results confirm that bark morphological complexity plays a key role in classification performance: species with distinctive bark patterns, such as *Vochysia haenkeana*, were classified more accurately, whereas species with convergent characteristics, including *Astronium fraxinifolium* and *Apuleia leiocarpa*, posed greater challenges. The presence of superficial elements (e.g., lichens and scars) and environmental variability also affected model performance by introducing visual noise. Despite these challenges, MobileNetV2 represents a valuable complementary tool for large-scale forest inventories and environmental monitoring. Its phenology-independent approach is particularly advantageous in seasonally dynamic biomes like the Cerrado, especially where botanical expertise is limited, contributing to more efficient

biodiversity assessments and conservation planning. However, this study has limitations, notably the use of data from a single seasonal period and the focus on species-level classification, highlighting the need for broader temporal coverage and taxonomic scope. Future research should expand the dataset across seasons and regions, integrate expert knowledge for iterative model refinement, and explore multimodal deep learning approaches combining multiple plant traits. Such advances could enhance accuracy, robustness, and the potential to extend bark-based identification beyond the species level, reinforcing the role of AI in biodiversity conservation.

Declarations

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CRediT authorship contribution statement

J.S.R: conceptualization, methodology, visualization, validation, data curation, formal analysis, writing-original draft. M.H.A.D.: Data curation and Formal analysis. C.M.S.N. and E.T.P.: supervision, resources, validation, writing-review and editing. All authors reviewed the manuscript.

Declaration of Interest Statement

The authors declare no competing interests.

Data availability statement

The datasets generated during and/or analyzed during the conduction of the study are available from the corresponding author upon reasonable request.

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Figures

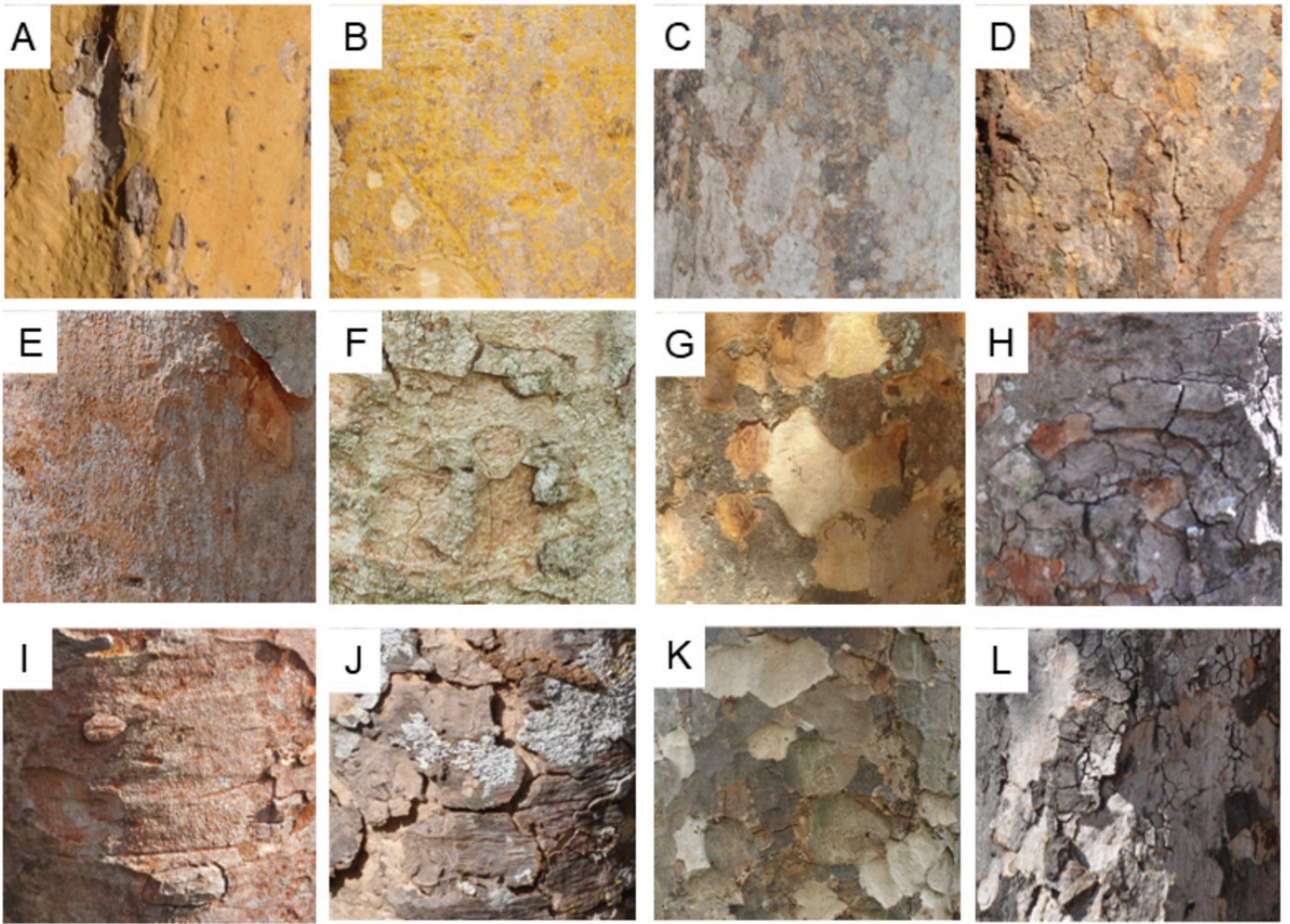


Figure 1

Representative examples of bark morphological variation within species and similarities between species. (A-D) Bark of *Vochysia haenkeana* (Vochysiaceae), illustrating intraspecific variation in texture and coloration. (E-H) Bark of *Apuleia leiocarpa* (Fabaceae), illustrating intraspecific variation in texture and coloration. (I-L) Bark of *Astronium fraxinifolium* (Anacardiaceae), illustrating intraspecific variation in texture and coloration. These detailed views highlight the complex morphological variations within each species and underscore the subtle similarities present between *Vochysia haenkeana*, *Apuleia leiocarpa* and *Astronium fraxinifolium* (e.g., compare panels F and J, or G and K), which contribute to identification challenges

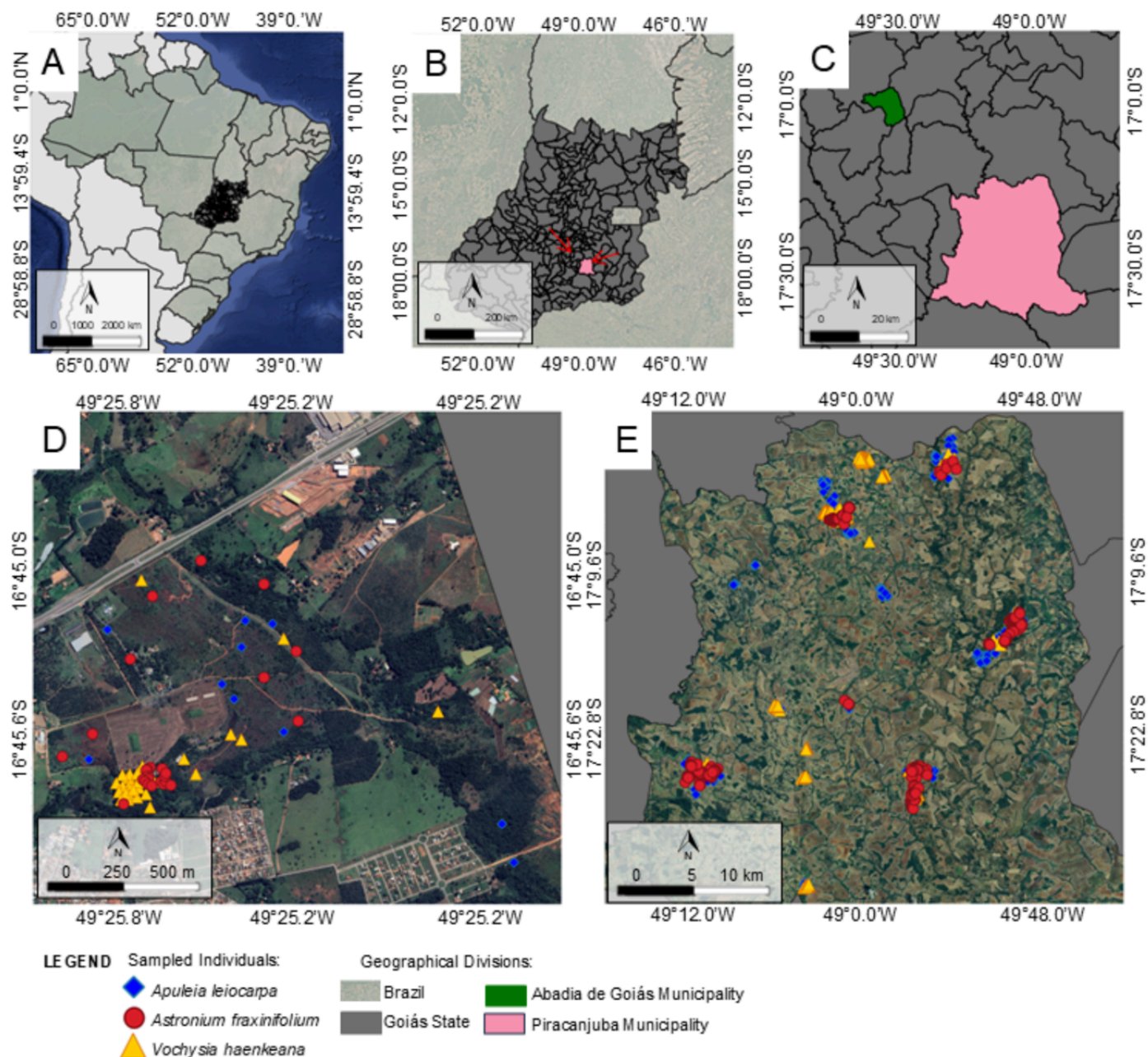


Figure 2

Spatial distribution of sampled tree individuals in the Brazilian Cerrado biome across nested geographical contexts. (A) Location of Goiás State within Brazil. (B) Overview of Goiás State. (C) Detailed map of sampled individuals in Abadia de Goiás municipality on satellite imagery. Points are color-coded by species: blue diamonds for *Apuleia leiocarpa*, red circles for *Astronium fraxinifolium*, and yellow triangles for *Vochysia haenkeana*. (D) Detailed map of sampled individuals in Piracanjuba municipality on satellite imagery. Points are color-coded by species: blue diamonds for *Apuleia leiocarpa*, red circles for *Astronium fraxinifolium*, and yellow triangles for *Vochysia haenkeana*. The map was prepared by JS Reis using the software QGIS v.3.38.2 (QGIS 2022) and the Landsate 8 satellite image.

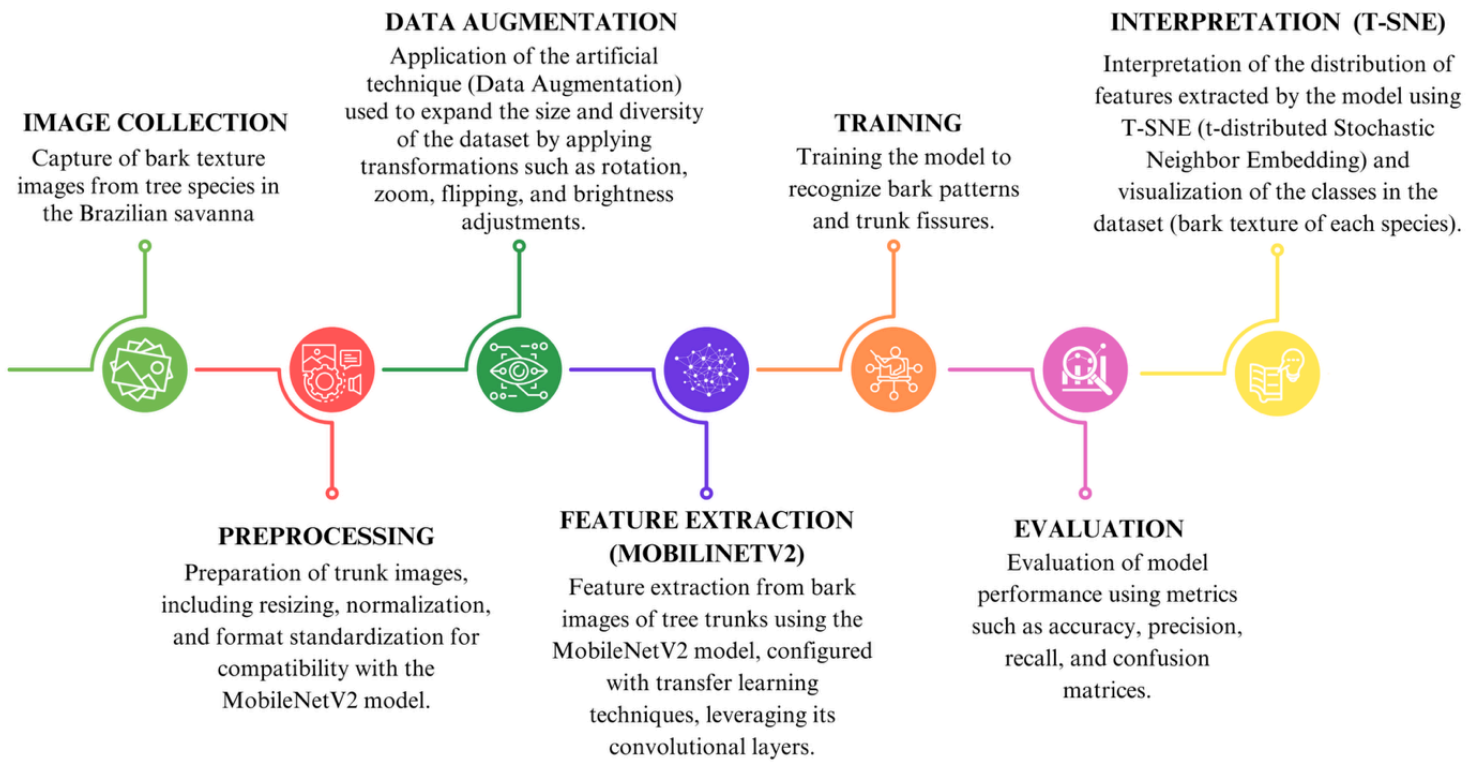


Figure 3

Overall methodological pipeline for bark image classification, illustrating the sequential workflow from image collection and preprocessing to model training, evaluation, and interpretation.

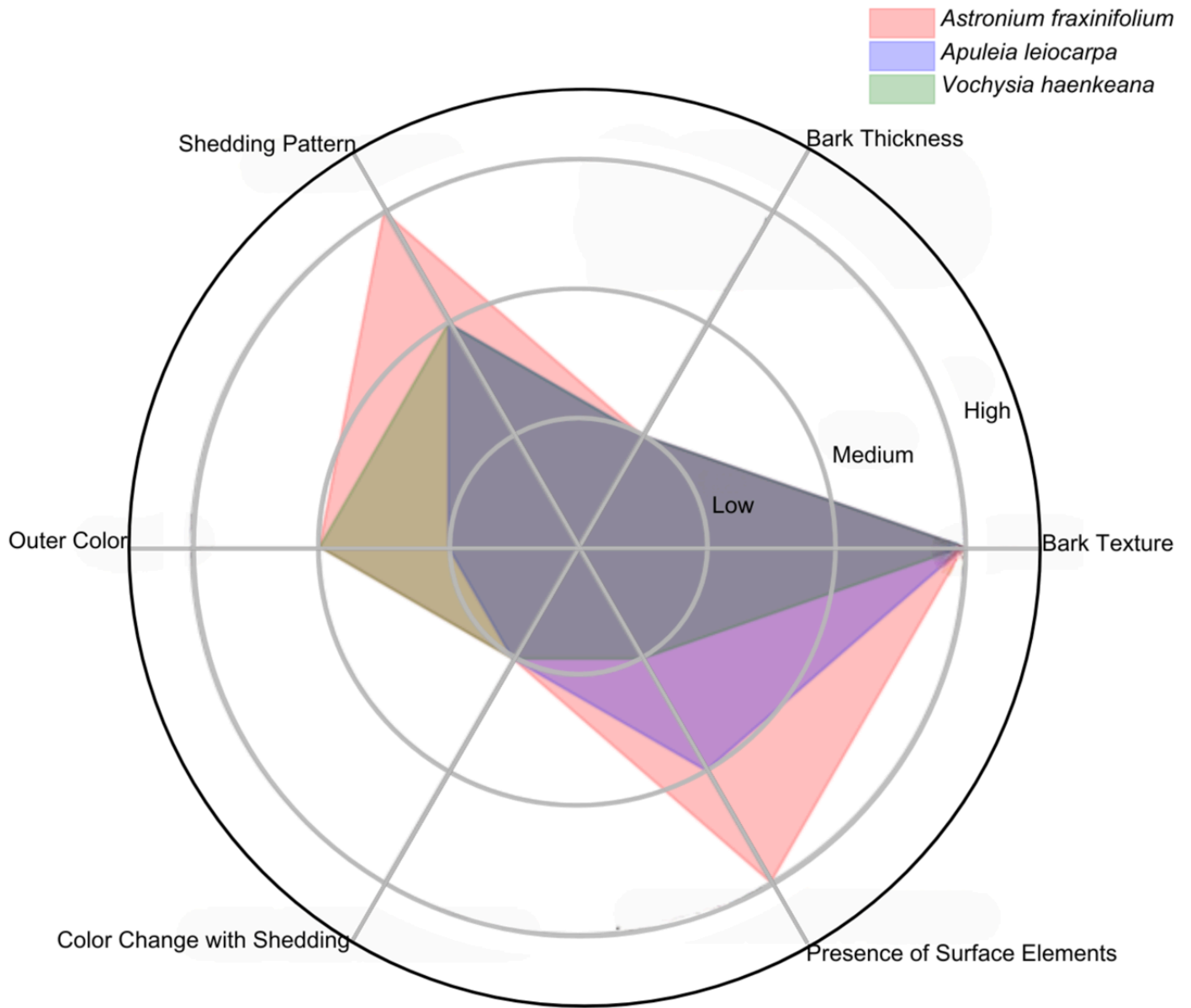


Figure 4

Qualitative assessment of key bark morphological characteristics for the three tree species: *Astronium fraxinifolium*, *Apuleia leiocarpa*, and *Vochysia haenkeana*. The analyzed dimensions include bark texture, bark thickness, shedding pattern, outer coloration, color change with shedding, and the presence of surface elements. These characteristics were visually assessed to represent the inherent morphological variability and distinctiveness among the species, which directly influenced the model's learning and differentiation challenges.

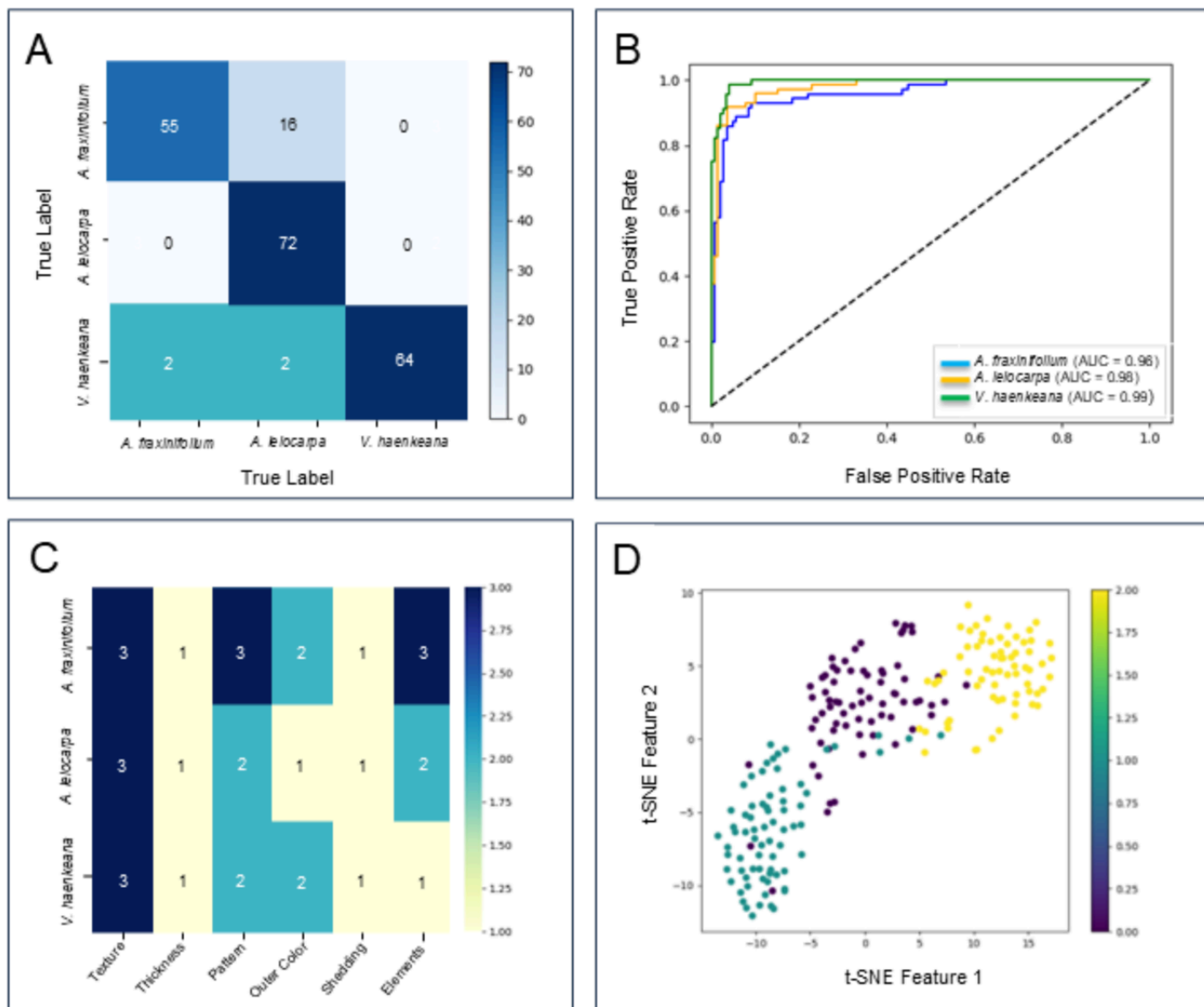


Figure 5

Comprehensive visualization of MobileNetV2 model performance and underlying bark characteristics for species classification. (A) Confusion Matrix: Displays the classification performance, showing true labels versus predicted labels for *Apuleia leiocarpa*, *Astronium fraxinifolium*, and *Vochysia haenkeana*. (B) Receiver Operating Characteristic (ROC) Curves: Illustrates the discriminative capabilities of the model for each species, with corresponding Area Under the Curve (AUC) values. (C) Heatmap of Bark Characteristics: Shows the distribution and visually assessed scores of key bark morphological characteristics across the three species. The numerical scale (1-3) represents a qualitative categorization of each bark trait's prominence or complexity, where 1 indicates low, 2 moderate, and 3 high prominence/complexity. This visualization highlights the inherent variability and similarities in bark traits influencing classification. (D) t-SNE Visualization: Displays the clustering (separation and overlap) of specific patterns extracted from the image samples in a two-dimensional space. Points represent

1,304 samples, color-coded by species: *A. fraxinifolium* (purple/blue), *A. leiocarpa* (green), and *V. haenkeana* (yellow). The x-axis represents t-SNE feature 1, and the y-axis represents t-SNE feature 2. This panel visually demonstrates the learned separability and inherent similarities among the species' bark features.