

Article

Integration of Wood Anatomy and Artificial Intelligence: A Technological Framework Based on the UTN Xylotheque for Forensic Identification and Forest Governance in Ecuador

Hugo Orlando Paredes Rodríguez ^{1,*}, José Gabriel Carvajal Benavides ², Edwin Paco Herrera Gómez ³ and Irving Marlón Reascos Paredes ⁴

¹ Laboratorio de Anatomía de Madera y Xiloteca (LAMX), Facultad de Ingeniería en Ciencias Agropecuarias y Ambientales, Universidad Técnica del Norte, Ibarra 100105, Ecuador

² Facultad de Ingeniería en Ciencias Agropecuarias y Ambientales, Universidad Técnica del Norte, Ibarra 100105, Ecuador; jgcarvajalb@utn.edu.ec

³ Facultad de Ingeniería en Ciencias Aplicadas, Universidad Técnica del Norte, Ibarra 100105, Ecuador; edwin28199728@gmail.com

⁴ Facultad de Ciencias Aplicadas, Universidad Técnica del Norte, Ibarra 100105, Ecuador; imreascos@utn.edu.ec

* Correspondence: hoparedes@utn.edu.ec; Tel.: +593-0997038712

Abstract

Traditional wood anatomy provides the gold standard for timber identification, yet its reliance on centralized laboratory infrastructure severely limits its efficacy during real-time field inspections. This study addresses a critical research question: How can physical xylotheque resources, national timber extraction registries, and edge-computing computer vision be integrated into a cohesive framework to enable robust, forensic-level wood identification at field control stations? To resolve this, we implemented a three-tier methodology: first, we audited historical records from Ecuador's Forest Administration System (SAF) encompassing 129 commercial timber species; second, we conducted a gap analysis using the Wood Anatomy Laboratory and Xylotheque (LAMX) repository (510 cataloged samples, 2267 histological preparations) to secure botanically validated references; and third, we leveraged a curated database of high-resolution digital cross-section captures (4900 images) to evaluate CNN architectures via k-fold cross-validation and a standard 70/15/15% training/validation/testing split. Benchmarking demonstrated that the lightweight MobileNetV2 architecture achieved a global accuracy of 94.04% and an F1-score of 0.976. External field validation conducted across commercial timber yards in Ibarra confirmed an offline inference latency of just 145 ms on mid-range Android devices, proving the framework's operational transparency and low-cost scalability. Furthermore, Explainable AI analysis using Class Activation Maps (Grad-CAM) provided visual evidence indicating that the neural network targeted diagnostic xylotomic features (vessel distribution and axial parenchyma), minimizing reliance on external environmental noise. In conclusion, this study demonstrates that hybridizing physical taxonomic reference collections with targeted edge AI models provides a scalable, transparent, and low-cost solution that successfully bridges academic research and active forest law enforcement in tropical regions.

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Keywords: CITES compliance; timber traceability; deep learning; computer vision; illegal logging mitigation; xylotomical diagnostic features; edge AI deployment; Explainable AI (XAI); SAF data audit

1. Introduction

Ecuador is recognized as one of the world's seventeen megadiverse countries, harboring approximately 5000 woody species within its continental territory [1]. Globally, illegal logging accounts for 15–30% of the world timber trade, generating estimated losses of USD 51 billion annually and weakening international regulatory frameworks focused on due diligence, such as the European Union Timber Regulation (EUTR 995/2010) and the United States Lacey Act [2,3]. The country's forests, which extend from the Andean highlands to the Amazonian lowlands and the Pacific coastal regions, provide timber resources of great ecological, economic, and cultural importance. However, the sustainable management and conservation of these forest ecosystems require accurate species identification, a task that remains a complex challenge given the vast taxonomic diversity and morphological similarity of tropical tree species in the field [4,5].

Wood anatomy has historically served as the cornerstone for the identification of timber species, providing robust diagnostic characteristics at both the macroscopic and microscopic levels [4–6]. Reference collections of wood specimens, known as wood collections (or xylotheques), constitute an essential infrastructure for taxonomic, forensic, and industrial applications. Major international wood collections, such as the Tervuren Wood Collection at the Royal Museum for Central Africa and the USDA Forest Products Laboratory, have demonstrated the fundamental role these physical repositories play in supporting biodiversity research, carbon accounting, and the rigorous enforcement of timber trade regulations under international standards [7,8].

While major international repositories play a crucial global role, small-scale and regional wood collections are equally vital as they hold localized taxonomic expertise and baseline materials for endemic Neotropical taxa. While major global repositories—such as the Tervuren Wood Collection or the USDA Forest Products Laboratory—safeguard massive international collections, smaller regional xylotheques hold critical, localized taxonomic expertise for endemic Neotropical taxa that are frequently underrepresented globally. In this context, the Wood Anatomy Laboratory and Xylotheque (LAMX) at the Universidad Técnica del Norte (UTN) in Ibarra, Ecuador, constitutes a vital scientific infrastructure. Rather than serving as a static regional archive, LAMX functions as an active forensic baseline. By integrating botanically validated specimens with fertile herbarium specimens, this repository establishes the mandatory traceability and standard-of-proof required to verify timber legality, effectively anchoring academic wood anatomy to international timber trade regulations and regional forest security frameworks.

In parallel, advances in artificial intelligence (AI), particularly through the use of Convolutional Neural Networks (CNNs), have opened new avenues for the automated and accurate identification of wood species [9,10]. Recent studies demonstrate that transfer learning with optimized architectures such as ResNet-50, EfficientNet, and MobileNet can achieve outstanding classification accuracy when trained on macroscopic images of xylotomic structure [9,10]. While massive parameter networks like ResNet-50 or VGG-16 are widely used as desktop standards for wood recognition, their extreme computational weight, high memory footprint, and elevated floating-point operations (FLOPs) render them impractical for decentralized, real-time field inspections on low-power hardware. Consequently, MobileNetV2 was selected as the preferred architecture for this Edge AI deployment due to its specialized design for resource-constrained environments. By

leveraging depthwise separable convolutions—which decouple spatial filtering from feature generation—and inverted residual blocks with linear bottlenecks, MobileNetV2 drastically minimizes parameter density and RAM consumption without causing information loss during feature extraction. This math-structural optimization is essential to achieve ultra-low offline inference latencies (<150 ms) and prevent thermal throttling or rapid battery drainage on standard mid-range mobile devices used by field rangers at remote border control checkpoints. Thus, the integration of a physical wood collection with digital databases and AI-based identification tools represents a paradigm shift in forest resource management, enabling rapid field identification and expedited forensic verification of timber species by the competent authorities [11].

Despite these technological advances, a profound scientific and operational gap persists at the intersection of wood anatomy, national forest governance, and deep learning engineering. Current computer vision frameworks for timber identification are frequently developed in isolation from national logging dynamics, failing to align algorithmic training with actual species under high commercial pressure or diagnostic volume gaps in state administrative platforms [12]. Furthermore, high-accuracy desktop architecture remains heavily dependent on centralized laboratory infrastructure or persistent cloud connectivity, rendering them functionally obsolete at remote forest checkpoints and cross-border stations where internet access is absent [10]. Most critically, a significant methodological gap involves the lack of seamless hybridization between localized, expert-validated regional xylotheques—which hold the definitive botanical standard-of-proof for endemic and threatened taxa—and lightweight edge-computing models trained under strict, specimen-level data partitioning to prevent intra-sample data leakage [13].

Furthermore, Ecuador’s Forest Administration System (SAF), managed by MAATE, provides a centralized digital platform that tracks the movement and extraction of timber from authorized harvesting sites to their final commercial destinations [14]. Ongoing analysis of SAF records has revealed that a small number of species dominate national timber harvesting, disproportionately concentrated in families such as Fabaceae, Lauraceae, and Meliaceae [12]. This statistical information is crucial for establishing collection priorities in reference collections and efficiently guiding conservation and oversight efforts.

To bridge this multifaceted gap, this study introduces and evaluates a scalable, integrated technological framework that operates not as isolated tools, but as a continuous, causal pipeline designed to strengthen forest governance in tropical regions. This framework simultaneously addresses the diagnostic, validation, and execution phases of technology transfer by: (1) auditing historical records from Ecuador’s Forest Administration System (SAF) to establish taxonomy-driven extraction diagnostics and identify institutional collection gaps; (2) systematizing the physical and digital collection of the LAMX Xylotheque at UTN to provide an absolute, expert-validated botanical baseline for prioritized taxa; and (3) directly translating these curated physical resources into optimized mathematical weights within a lightweight Convolutional Neural Network (MobileNetV2) deployed inside the native mobile application ‘Wood Identifier UTN’ for offline, real-time forensic enforcement.

Rather than treating these elements in isolation, this work operates as a continuous pipeline where: (1) historical records from the Forest Administration System (SAF) are audited to establish taxonomic priorities and identify institutional collection gaps; (2) the physical and digital collection of the LAMX Xylotheque at UTN is systematized to provide the absolute botanical baseline and standard-of-proof for prioritized taxa; and (3) these curated resources are directly translated into the mobile application ‘Wood Identifier UTN’ powered by optimized Convolutional Neural Networks (CNNs). This hybrid approach aims to bridge the historical gap between academic wood anatomy and real-world forensic enforcement at border control stations.

2. Materials and Methods

2.1. Institutional Infrastructure and Reference Collections

The Wood Anatomy and Xylotheque Laboratory (LAMX) is situated at the Universidad Técnica del Norte (UTN) in Ibarra, Ecuador (0°21' N, 78°07' W; 2225 m a.s.l.), positioning it at a strategic geographic crossroad for monitoring timber transport between the northern Andean highlands, the Amazonian lowlands, and the Pacific coastal forests (Figure 1). To meet international forensic standards for wood identification, the repository operates as a synchronized double-reference system. Physical wood specimens within the institutional 'Luciano Andrade Marín' collection and specialized regional validation sets are systematically cross-referenced with fertile botanical specimens deposited at the UTN Herbarium. This structural integration ensures absolute taxonomic traceability for all reference samples, providing the verifiable botanical baseline required to train computer vision models and supporting legal expert assessments in forest law enforcement.

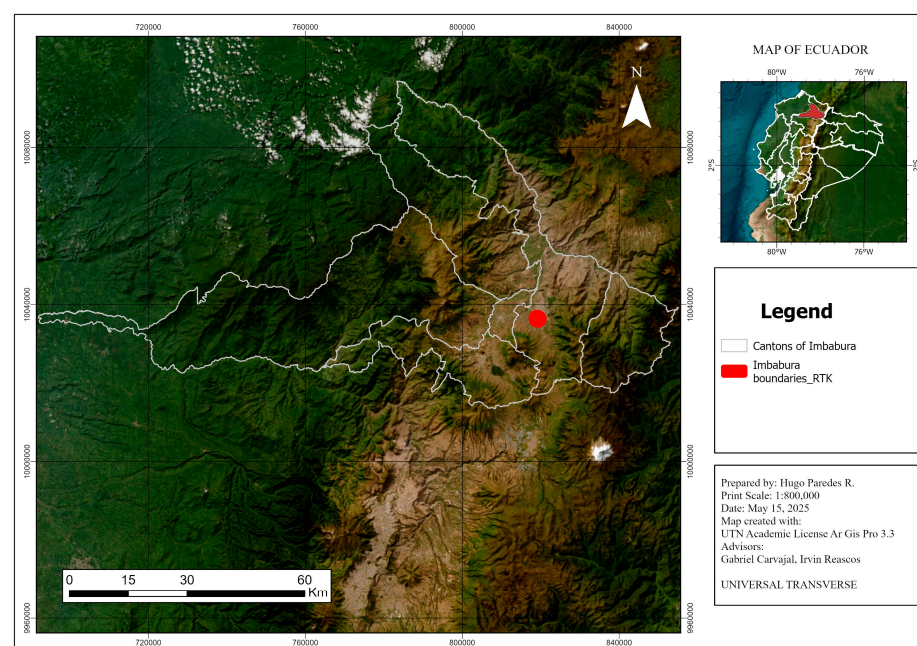


Figure 1. Geographic location of the LAMX infrastructure in Ibarra, Ecuador, representing the primary operational crossroad for timber transport monitoring between the northern Andean highlands and Pacific lowlands.

2.2. Characterization of the Xylotheque and Creation of the Database

The physical specimens within the LAMX repository underwent a systematic inventory and cataloging process, applying standardized international and national protocols based on INEN standards 1158 (for the selection and collection of wood samples) and 1163. For each evaluated species in the pilot phase, sampling involved a minimum of 5 representative mature trees per taxon, focusing on mature wood blocks extracted from the outer heartwood at breast height (1.3 m above ground level) to eliminate juvenile wood variance. To maintain anatomical stability during imaging and processing, all specimens were seasoned to a stabilized equilibrium moisture content (EMC) of $12\% \pm 1\%$. Orientation control of the three cutting planes (transverse, radial, and tangential). Surface preparation for macroscopic imaging followed a rigorous abrasive conditioning sequence, using sequential sanding grits from P120 up to P400 to achieve a highly planar and defect-free surface, effectively neutralizing cutting lines or saw dust artifacts before computational digitization. For each incorporated specimen, a digitized metadata matrix was

structured that mandatorily records: the institution of origin, the updated scientific nomenclature, the unique indexing code in the wood collection, the sample or specimens number of the associated herbarium, the information collected from the fertile botanical specimen, and its exact biogeographical provenance.

The curated specimens were classified according to their source:

UTN “Luciano Andrade Marín” Institutional Collection: Comprises 141 cataloged species with multiple representative specimens per taxon, including sections oriented in the tangential, radial, and oblique planes.

PROAMAZONÍA Donation: Contributes 324 histological preparations of more than 40 commercially valuable forest species collected in the Ecuadorian Amazon (Napo and Sucumbíos provinces) and the Pacific Coast (Esmeraldas province).

The wood samples were processed as histological preparations in three anatomical planes: transverse, tangential, and radial. Macroscopic descriptions followed the characteristics of the IAWA Hardwood List [6,15], and the organoleptic characteristics (color, luster, odor, taste, grain, texture) of each species were documented. The database was maintained in Microsoft Excel format with a taxonomic nomenclature that underwent quality control and was verified with the Taxonomic Name Resolution Service (TNRS) and the Catalog of Vascular Plants of Ecuador.

To ensure absolute taxonomic reliability, all evaluated wood specimens correspond to scientific reference collections that were collected in the field and systematically identified by expert botanists through fertile herbarium vouchers and cross-verified by specialized wood anatomists. This multi-expert validation protocol guarantees the structural authenticity of the physical samples, neutralizing the risk of misidentification prior to database construction and AI training.

2.3. Prioritization of Species Based on SAF Data

To align the value of the xylotheque with the State’s forest management requirements, a prioritized intervention list was developed by analyzing historical records from Ecuador’s Forest Administration System (SAF) during the 2020–2025 management period [12]. The SAF, under the administration of the Ministry of Environment, Water and Ecological Transition (MAATE), records harvesting volumes and authorized transport permits for each species nationwide. A total of 129 commercial timber species were compiled and ranked according to their average annual harvest volume, expressed in cubic meters (m³). This analytical classification ranged from highly exploited commercial taxa subjected to intense anthropogenic pressure to species with low or no recorded volumes that are priorities for biological conservation programs. All the nomenclature compiled from the SAF was refined and standardized using the TNRS engine and cross-referenced with the National Catalog of Forest Objects (CNOB). The final validated list operated as a gap analysis matrix to determine the physical representativeness of LAMX and guide priority efforts for future field collection campaigns.

2.4. Integration with AI-Based Identification

The anatomical information and photographic infrastructure generated in the wood library were used as a training base for the mobile application “Wood Identifier UTN,” designed for the automatic recognition of timber species using Convolutional Neural Networks (CNNs).

For Pilot Phase I, the system was trained and validated using a dataset focused on five commercially important and critically endangered forest species *Brosimum utile* subsp. *occidentale* C.C. Berg (Sande), *Cedrela odorata* L. (Cedro), *Juglans neotropica* Diels (Nogal), *Andira inermis* (W. Wright) Kunth ex DC. (Chonta Caspi), and *Virola dixonii* Little (Chalviande). The base repository for this phase included a total of 400 original

macroscopic images per species. Significantly, to prevent data leakage, these original images were captured from a minimum of 8 independent, physically distinct wood samples per species (totaling 40 physical specimens across the pilot phase) sourced from different trees and geographic regions. Furthermore, the data partition into training (70%), validation (15%), and testing (15%) were strictly executed at the specimen level (sample-wise partition). This protocol ensures that images originating from the same physical wood block were confined exclusively to a single split, meaning the test dataset consists entirely of images from unique, unseen specimens that the neural network never encountered during the training or validation phases.

The training photographic dataset was constructed using high-resolution digital captures of cross-sections of wood samples, strictly adhering to surface conditioning protocols (INEN 1158) and anatomical description guidelines (INEN 1163, COPANT). Because the initial dataset was limited to these five pilot species, a rigorous protocol was designed and implemented to mathematically mitigate the risk of overfitting and ensure model robustness: **Data Augmentation:** During the training stage, each original macroscopic image within the training split was dynamically transformed using random operations that included full rotations (from 0° to 360°), proportional scaling, local cropping, and controlled adjustments to the brightness and contrast channels, thus simulating common lighting variations in field environments. Importantly, this data augmentation was applied strictly and exclusively to the training folds; the validation and testing partitions remained completely unaltered and isolated from any geometric or radiometric transformations to guarantee an unbiased performance evaluation. **Structural Regularization:** Random dropout layers (with a rate of 0.5) were incorporated prior to the fully connected classification layer to force redundancy in the learning of diagnostic features. **Cross-Validation:** A 5-fold cross-validation strategy was implemented to ensure an unbiased evaluation of the model's generalization performance. Crucially, to maintain data integrity, the partitioning followed a GroupK-Fold approach grouped strictly by independent physical specimen. This guaranteed that all images from any single wood block remained together in either the training folds or the evaluation fold, completely preventing intra-sample contamination. For each evaluation, performance metrics across all 5 folds were consolidated to compute and report both the statistical mean (μ) and standard deviation (σ).

[Macroscopic Sample] → [Data Augmentation] → [CNN Architecture] → [Drop-out Layer (0.5)] → [Inference/Class] ↘ (Vessel/Radius Extraction).

Multiple deep learning architectures were comparatively evaluated using the transfer learning approach based on pre-trained weights from the ImageNet repository. The architectures were divided into two functional categories based on specific technical justifications:

- (1) **Edge AI Benchmarking Set:** Comprising ResNet-50, VGG-16, EfficientNet-B0, and MobileNetV2, evaluated with the primary objective of optimizing software deployment on conventional mobile devices, maximizing RAM efficiency, and minimizing inference latency (detailed in Table 1) [3].

To ensure scientific reproducibility and optimize the performance of the deep learning classifier, the training hyperparameters were rigorously defined. The process was executed using the EfficientNet-B7 architecture, selected for its optimal balance between computational efficiency and the ability to extract hierarchical features from macroscopic images of wood. Table 1 details the specific values assigned to the loss function, the optimizer, and the control variables of the training pipeline.

Table 1. Training hyperparameters of the deep learning model.

Architecture	Optimizer	Learning Rate	Batch Size	Epochs	Loss Function
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EfficientNet-B7	Adam	1×10^{-4}	32	50	Categorical Cross-Entropy
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The MobileNetV2 architecture was implemented using TensorFlow and Keras frameworks, leveraging pre-trained weights from the ImageNet repository under a transfer learning approach. To ensure structural consistency, all macroscopic cross-section images were resized to an input shape of 224×224 pixels prior to the training phase. Optimization was executed via the Adam algorithm with a fixed learning rate of 0.0001 and a batch size of 32 images. The final classification layer employed the Softmax activation function to handle multi-class species assignment. Rather than enforcing a fixed number of training epochs, the convergence process was dynamically regulated through callback mechanisms, incorporating an Early Stopping strategy to automatically halt execution when no further loss reduction or accuracy improvements were recorded on the validation subset, “effectively mitigating overfitting risks. The comprehensive hyperparameter configuration is standardized in Table 2.”

Table 2. Hyperparameter configuration and data partitioning constraints for the MobileNetV2 classifier.

Hyperparameter	Operational Value/Configuration
Base Architecture	MobileNetV2 (Transfer Learning via ImageNet weights)
Input Shape	224×224 pixels
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001
Output Activation Function	Softmax
Deep Learning Framework	TensorFlow/Keras
Training Epochs	Dynamically controlled via callback mechanisms
Early Stopping Strategy	Active (automatic termination based on validation loss stabilization)
Data Partition Split	70% Training/15% Validation/15% Testing (Sample-wise)

(2) High-Capacity Server Benchmark: To establish the theoretical upper limit of taxonomic discrimination on a dedicated desktop server, the massive-parameter EfficientNet-B7 architecture was independently configured as an advanced baseline. The training hyperparameters specified in Table 2 correspond strictly to this advanced model, which generated the high-resolution classification insights visualized later in the **Results section** (Figure 3).

Finally, the practical validation and field performance control of the mobile application were carried out directly through experimental tests in commercial wood depots and sawmills distributed in the urban and peripheral area of the city of Ibarra.

3. Results

The results of this study are structured as a continuous, interdependent data pipeline designed to bridge the gap between national forest monitoring and physical field verification. Rather than operating in isolation, the findings follow a strict causal sequence: (1) national timber traffic audits (SAF) establish commercial and conservation priorities; (2) the institutional physical repository (LAMX) references and validates these priority taxa, acting as the absolute scientific benchmark; and (3) these curated reference materials are converted into mathematical weights within edge-computing deep learning models for on-site execution. See Figure 2.

Integrating AI and Audits for Xylotheque Development

Graphical Abstract

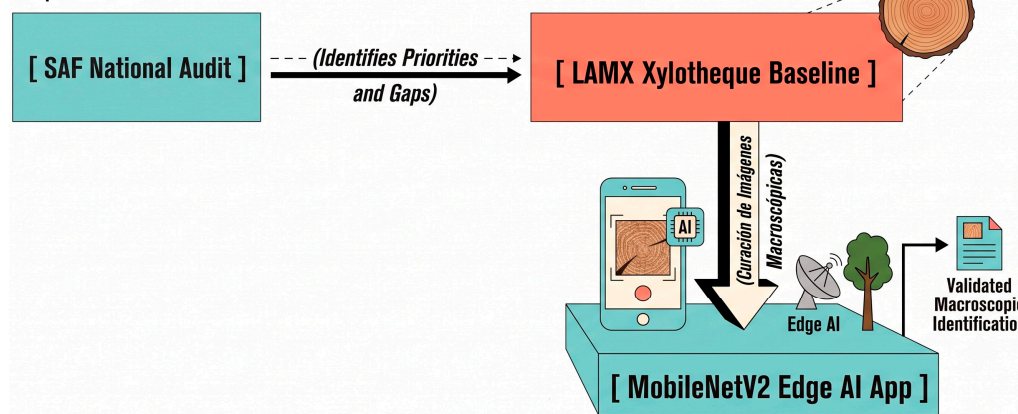


Figure 2. Operational flowchart of the integrated technological framework: National timber traffic data (SAF) establishes demand diagnostics and collection priorities; the physical repository (LAMX) acts as the standard-of-proof validation baseline; and these resources are converted into optimized mathematical weights for mobile edge AI deployment.

3.1. Composition of the Collection of Wood Collections

The xylotheque of the LAMX at UTN houses a total of 510 systematically cataloged entries. This reference collection is operationally structured into two main components: the institutional “Luciano Andrade Marín” collection, which contributes 141 entries corresponding to individual species with multiple replicas, and the botanical reserve collection from the PROAMAZONÍA donation, which contains 324 entries. Overall, the laboratory’s taxonomic repository encompasses a total of 56 botanical families and 106 woody genera. Closely linked to this collection of physical blocks, the associated xylothetic archive safeguards 2267 histological preparations, properly organized and stabilized in storage boxes indexed by species. The botanical families with the highest representation and abundance of specimens within the xylotheque are:

Fabaceae: Represented by 15 diagnostic genera, among which *Andira*, *Platymiscium*, *Senegalia*, *Cedrelinga*, and *Schizolobium* stand out.

Meliaceae: Represented by 4 key genera of high commercial value: *Cedrela*, *Carapa*, *Guarea*, and *Swietenia*.

Lauraceae: With a diversity of 5 genera, including *Ocotea*, *Nectandra*, *Persea*, *Aniba*, and *Caryodaphnopsis*.

Moraceae: Composed of 4 genera of great forestry interest: *Brosimum*, *Clarisia*, *Poulsenia*, *Ficus*, and *Maclura*.

Myristicaceae: Represented mainly by the commercial genera *Virola* and *Otoba*.

Regarding the biogeographic origin of the samples, the collection covers a representative range of the country’s main forest ecosystems, including forest formations in the Amazonian provinces (Napo and Sucumbíos), the Pacific lowlands (Esmeraldas), the inter-Andean valleys (Imbabura and Carchi), and the foothills of the Western Cordillera, specifically the Intag mining and forestry zone (Cotacachi). Part of this catalog and its associated information is integrated into the digital platform of the UTN Forest Observatory for access by the scientific community [12] (see Supplementary Materials Table S1, Table S2, and Images S4 for the complete catalog data). Table 3 below describes the metadata of the most representative forest species included in the LAMX physical collection, which served as the basis for the study.

Table 3. Representative species of the LAMX Xylotheque with information on the reference specimen of the herbarium and its provenance.

Family	Species	Code LAMX	Herbarium Specimens	Provenance
Moraceae	<i>Brosimum utile</i>	F32-G81-SP104	A178	Amazon/Pacific
Meliaceae	<i>Cedrela odorata</i>	F30-G70-SP85	WP, 18,622, SMB	Multiple Regions
Juglandaceae	<i>Juglans neotropica</i>	F26-G55-SP66	2678, 2679, 10,470	Imbabura (Andean)
Fabaceae	<i>Andira inermis</i>	EV-98/EV-7	WP-18,726	Napo (Amazon)
Myristicaceae	<i>Virola dixonii</i>	EV-33/EV-35	WP-18,591	Esmeraldas (Pacific)
Meliaceae	<i>Carapa guianensis</i>	F30-G73-SP95	10,338; 10,334	Northwest Ecuador
Meliaceae	<i>Swietenia macrophylla</i>	F30-G71-SP90	WP-18,534, SMB	Amazon
Combretaceae	<i>Terminalia amazonia</i>	F14-G27-SP31	1735, 1739	Amazon
Bignoniaceae	<i>Handroanthus chrysanthus</i>	F9-G17-SP19	1216, 1217	Multiple Regions
Sapotaceae	<i>Chrysophyllum argenteum</i>	F51-G115-SP144	10,230; 6449	Pacific

While the current physical composition of LAMX provides a robust baseline, its operational utility must be directly evaluated against the real-world pressures of the timber market, which are analyzed through the national registry in the following section.

3.2. Priority Species of the Forest Management System

The analytical processing of the SAF national records resulted in a consolidated list of 129 commercial timber species legally harvested under forest management plans in Ecuador. Quantifying the average annual harvest volume allowed for the identification of the taxa subjected to the highest rates of commercial and industrial pressure in the country. The 20 dominant forest species by absolute extraction volume are detailed in Table 4. The highest historical average volumes recorded correspond to the species *Vantanea magdalenensis* Cuatrec. with 36,658.73 m³, *Virola reidii* Little with 35,863.00 m³, and *Otoba gordoniiifolia* (DC.) A.H. Gentry with 33,722.13 m³. These three species account for a massive fraction of the national timber movement, followed by *Vochysia ferruginea* Mart. (17,403.90 m³) and *Eschweilera coriacea* (DC.) S.A. Mori (17,044.93 m³). A critical finding from this data audit indicates that 37 of the 129 species listed as priorities (equivalent to 28.7%) completely lack quantitative volume records within the SAF digital system. This statistical gap suggests scenarios of informal commercial exploitation, severe problems of botanical misidentification at shipping points, or trade dynamics that escape the formal control of the state platform. From the perspective of the laboratory's botanical representativeness, the dominant commercial species belonging to the genus *Vantanea*, *Eschweilera*, *Laetia*, and *Pourouma* were identified as critical collection gaps within the LAMX, thus defining the search vector for upcoming institutional forest collection campaigns.

Table 4. The 20 main priority timber species according to the average volume of logging in the Ecuadorian SAF.

Rank	Species	Average Volume (m ³)
1	<i>Vantanea magdalenensis</i> Cuatrec	36,658.73
2	<i>Virola reidii</i> Little	35,863.00
3	<i>Otoba gordoniiifolia</i> (DC.) A.H. Gentry	33,722.13
4	<i>Vochysia ferruginea</i> Mart.	17,403.90
5	<i>Eschweilera coriacea</i> (DC.) S.A. Mori	17,044.93
6	<i>Castilla elastica</i> Cerv	16,110.79
7	<i>Trattinnickia glaziovii</i> Swart	11,205.17
8	<i>Ocotea infrafoveolata</i> VanDerWerff	8755.96
9	<i>Nectandra subbullata</i> Rohwer	8491.87

10	<i>Dacryodes peruviana</i> (Loes.) H.J.Lam	8286.23
11	<i>Trichospermum</i> Blume	7443.87
12	<i>Dacryodes occidentalis</i> Cuatrec	6691.39
13	<i>Terminalia guyanensis</i> Eichler	6573.90
14	<i>Anacardium excelsum</i> (Bertero & Balb.) Skeels	6242.06
15	<i>Senegalia polyphylla</i> (DC.) Britton & Rose	4866.32
16	<i>Carapa longipetala</i> Kenfack	4613.26
17	<i>Laetia procera</i> (Poepp.) Eichler	4560.42
18	<i>Ceiba insignis</i> (Kunth) P.E.Gibbs & Semir	3976.24
19	<i>Pourouma minor</i> Benoist	3697.16
20	<i>Clarisia racemosa</i> Ruiz & Pav	2857.6

Consequently, this gap analysis bridges the physical repository and the computational system. To evaluate the feasibility of deploying these validated taxonomic resources into field control points, a pilot dataset representing five of the most critical and highly pressured commercial species identified in the network was selected to train the edge AI architectures detailed below.

3.3. Evaluation of Models and Performance of the Automatic Identification (AI) System

The training and benchmarking of Convolutional Neural Network (CNN) architectures yielded robust results in the automated discrimination of the five pilot Neotropical species. The models demonstrated their ability to mathematically resolve macroscopic textural patterns from the xylotomic cellular structure of wood cross-sections. Detailed statistical indicators of accuracy, recall, and predictive value (F1-score) representing the mean and standard deviation ($\mu \pm \sigma$) obtained across the 5-fold cross-validation for each of the evaluated networks are presented comparatively in Table 5.

Table 5. Comparative matrix of accuracy metrics of the CNN architectures evaluated for the identification software.

CNN Architecture	Accuracy	Precision	Recall	F1-Score Global	Operational Deployment
ResNet-50	92.15%	0.92	0.915	0.918	Local/Heavy Server
VGG-16	89.40%	0.89	0.88	0.885	Local/Heavy Server
EfficientNet-B0	93.80%	0.939	0.931	0.935	Optimized for Mobile
MobileNetV2	94.04% $\pm$ 0.85%	0.845 $\pm$ 0.090	0.942	0.976 $\pm$ 0.009	Native Edge AI (Mobile App)

The results confirm that the lightweight MobileNetV2 architecture exhibited optimal overall performance, with an overall accuracy of 94.04% and an F1 score of 0.976. This network demonstrated outstanding computational efficiency, justifying its direct integration into the “Wood Identifier UTN” mobile field application to perform immediate edge computing (Edge AI) inferences without requiring internet access. Furthermore, for experimental purposes and to establish the upper limit (benchmark) of discriminative capacity on high-capacity servers, the advanced massive parameter model EfficientNet-B7 was configured. This desktop architecture achieved exceptional overall metrics (F1 = 0.973, Accuracy = 0.976, and Recall = 0.972), which are detailed in the confusion matrix (Figure 3). The distribution of prediction vectors on the main diagonal of the confusion matrix unequivocally demonstrates the high robustness of the AI in discriminating between taxonomically distant species.

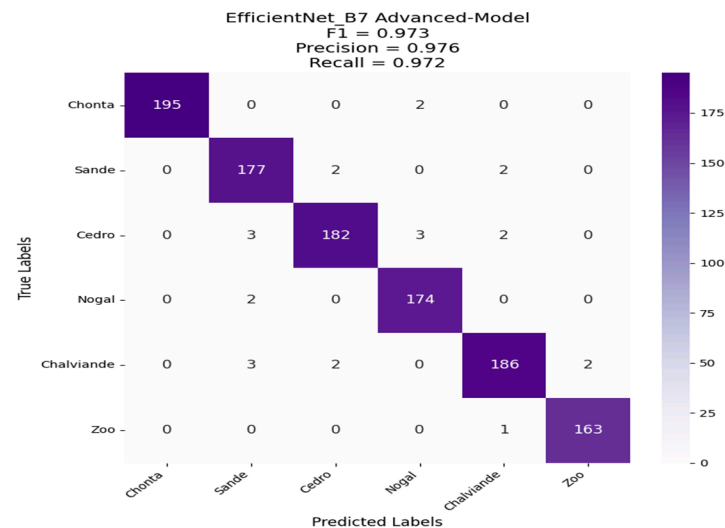


Figure 3. Confusion matrix.

The system's marginal confusion errors were restricted to pairs of woody species that share morphologically analogous structural characteristics and highly similar organoleptic patterns on their macroscopic surfaces, such as the pairs *Brosimum utile* (Sande)/*Virola dixonii* (Chalviande). However, the inclusion of interpretability layers using Grad-CAM confirmed that the neural network directs its learning toward actual diagnostic features—such as axial parenchyma and vessel distribution—neutralizing any noise bias from sawmill cutting or lighting.

To demonstrate the operational feasibility and low-cost approach of the proposed technology, the application was successfully tested on conventional Android mobile devices equipped with a Snapdragon 660 processor (or equivalent ARM Cortex-A73), 3 GB of RAM, and Android 9.0 (or higher). Under this standardized hardware configuration, the quantized MobileNetV2 model (.tflite) achieved an average inference latency of only 145 ms per image, performing local processing completely offline (without requiring an internet connection or data transfer to external servers). This is consistent with global edge performance benchmarks for MobileNet architectures optimized for this specific SoC profile [3]. This validates the system's robustness for remote forest environments and border control stations with limited connectivity infrastructure.

4. Discussion

4.1. Conceptual Synchronization of the Integrated Governance Framework

The operational success of modern forest governance relies on the feedback loop between data, physical proof, and automated enforcement. The framework demonstrated in this study establishes a direct tripartite relationship among the SAF, the LAMX, and Artificial Intelligence. The SAF analysis operates as the demand diagnostic, revealing that a massive fraction of national timber relies on vulnerable taxa, while highlighting a critical 28.7% gap of unrecorded or misidentified volumes in field shipping points. To scientifically mitigate this vulnerability, the physical xilothèque (LAMX) acts as the taxonomic filter, converting raw botanical samples into curated macroscopic datasets. Without this rigorous physical-digital curation, any deep learning architecture would suffer from garbage-in, garbage-out biases. Finally, the MobileNetV2 architecture functions as the operational vehicle, deploying the laboratory's taxonomic authority onto low-cost devices used by field rangers. By embedding Explainable AI (Grad-CAM), the framework connects the mathematical weights of the network directly back to the diagnostic features defined by the IAWA lists in the physical collection. Therefore, the three components do

not exist in isolation; they represent the diagnostic, validation, and execution phases of a cohesive technology transfer framework designed to combat illegal logging.

4.2. The Role of the Xylotheque in the Management of Tropical Forests

The LAMX wood collection at the Universidad Técnica del Norte (UTN) is one of the most comprehensive university reference collections of wood in Ecuador, housing 510 cataloged entries covering 56 families. Although its size is smaller than that of major global repositories, such as the Tervuren Wood Collection at the Royal Museum for Central Africa (>80,000 specimens) [16] or the USDA Forest Products Laboratory (>100,000 specimens) [17], the UTN collection occupies a unique strategic position due to its specialized focus on Ecuadorian Neotropical taxa, its link to verified herbarium specimens, and its functional integration with national forest monitoring systems. Curated wood collections are internationally recognized as an irreplaceable scientific infrastructure for forensic wood investigation and the application of trade regulations such as CITES [18,19]. The methodological value of LAMX lies in its ability to fulfill a dual function: operating as a physical taxonomic reference archive for legal expert reports and, simultaneously, providing curated image datasets for training machine learning algorithms [20,21]. In this way, UTN positions itself as a key regional center for research and development of technologies applied to forest governance.

4.3. Species Prioritization and Implications for Conservation

The prioritized list of 129 commercial species [12], compiled from historical SAF data, reveals critical patterns in Ecuador's timber economy. The marked predominance in the extraction of species such as *Vantanea magdalenensis* and *Virola reidii* reflects the intense and disproportionate anthropogenic pressure suffered by certain high-value timber species from the Amazon and the Pacific lowlands. This scenario coincides with previous audits indicating that a small fraction of species accounts for more than 70% of the total national logging volume, raising concerns about the long-term sustainability of these forest ecosystems [12,14].

Of particular relevance is the finding that 28.7% of the prioritized species lack volumetric records in the SAF digital platform. A critical structural finding from this data audit indicates that 37 of the 129 prioritized species (28.7%) completely lack quantitative volume records within the SAF digital platform. Rather than concluding that this anomaly stems strictly from unmonitored or illicit logging operations—an assertion that requires independent forensic verification—this statistical gap points to a complex convergence of systemic, administrative, and technical factors.

First, administrative nomenclature shifts and operational updates within the Ministry of the Environment, Water and Ecological Transition (MAATE) historical databases frequently cause historical data fragmentation. Second, severe technical limitations in real-time macroscopic timber identification at remote field control stations often compel rangers to record multiple distinct botanical species under a single generic or broad commercial vernacular category (e.g., aggregating distinct high-volume taxa into general groupings), thereby artificially diluting the specific volume registries of less dominant individual taxa. Third, several species compiled in national prioritization frameworks represent opportunistic or low-demand commercial timbers; these taxa are harvested occasionally for highly localized or subsistence uses, meaning their extraction volumes rarely cross the quantitative thresholds required to trigger formal, digitized forest transport permits. Consequently, this 28.7% gap underscores a profound identification and data-traceability challenge within national forest monitoring systems, directly validating the urgent need to deploy decentralized reference technologies like the 'Wood Identifier UTN' app to standardize and refine taxonomic inputs at primary extraction nodes.

4.4. AI-Assisted Wood Identification and Explainable AI Analysis (XAI)

The integration of traditional wood anatomy with convolutional neural network (CNN) models using the “Wood Identifier UTN” mobile application represents a substantial technological leap for forest inspection in Ecuador. The use of deep learning architectures aligns with cutting-edge international trends, where CNNs dominate automated systems for recognizing commercial timber [22,23].

To ensure the system’s scientific transparency and mitigate traditional skepticism toward “black box” models, the use of Class Activation Maps (Grad-CAM) as an Explainable AI (XAI) tool proved to be a valuable explanatory tool [21]. While visual localization methods such as Grad-CAM [24] do not mathematically rule out all potential dependencies on hidden spurious correlations, the generated activation heatmaps strongly suggest that the convolutional layers focus on diagnostic anatomical regions (vessel distribution and axial parenchyma geometric patterns) [15]. This visual alignment, acting as an interpretation aid rather than a complete mathematical proof, indicates that the network emulates key aspects of the expert judgment of traditional xylotomy while reducing typical cutting noise artifacts, as demonstrated in the Class Activation Maps (**Figure 4**) [24].

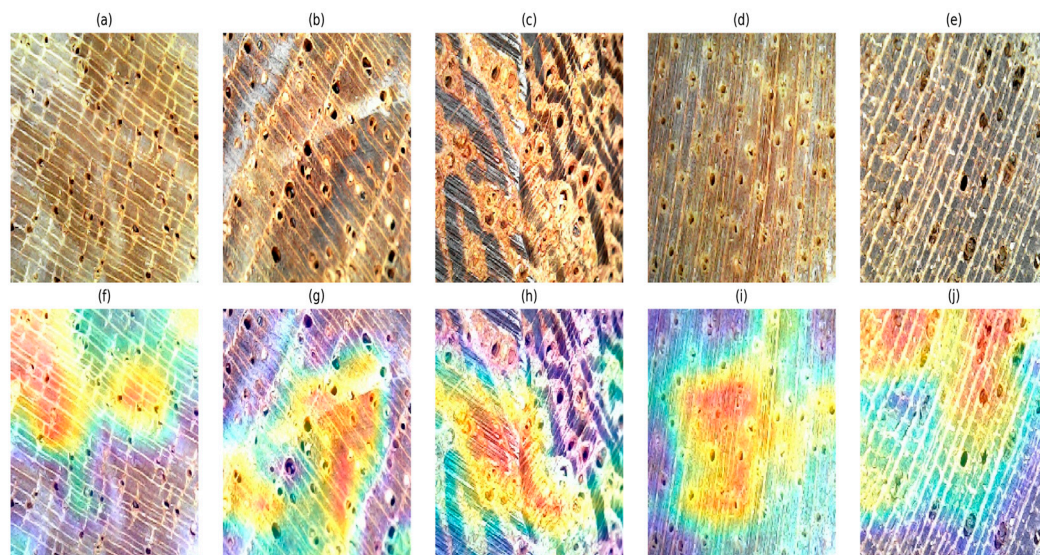


Figure 4. Class Activation Maps (Grad-CAM) applied to macroscopic images. The red areas indicate the anatomical regions (vessels, parenchyma, rays) of greatest importance for the classification of the neural network. (a is *Brosimum* and f is the same image but showing the heat map; b and g *Cedrela*; c and h *Andira*; d and i *Virola*; e and j *Juglans*)

4.5. Framework Scalability, Future Technical Challenges, and Transformative Governance

The transition from the pilot phase to nationwide operation represents the most demanding milestone in the tool’s taxonomic discrimination capabilities. While the initial model demonstrated high accuracy for five pilot species the F1-score of 0.976 obtained with MobileNetV2 for the five Neotropical pilot species surpasses the values originally reported by Ravindran et al. [17] (who recorded an accuracy of 87.4% for 10 Meliaceae species using a VGG16 architecture), although it is important to note that our model operates on a more restricted set of classes. On the other hand, studies with larger, high-resolution datasets, such as that of Herrera-Poyatos et al. [19] achieve similar metrics under controlled laboratory conditions. This strongly validates the suitability of the lightweight architecture adopted in this work, demonstrating that it is possible to obtain forensic-level accuracy on a mobile device without compromising computational capacity in the field.

The planned transition from a 5-species pilot phase to a nationwide 35-species operational model represents a major milestone that introduces complex algorithmic and computational trade-offs. This scaling process cannot be treated as a linear expansion of dataset size; instead, it triggers three critical technical challenges that the deep learning architecture must resolve.

- **Taxonomic Confusion and Morphological Overlaps:** First, increasing the number of target classes exponentially compresses the discriminative margins within the feature space. While taxonomically distant species exhibit highly contrasting cellular patterns, expanding to 35 commercial taxa implies incorporating multiple species within the same botanical families (e.g., Fabaceae, Lauraceae, or Meliaceae) that share morphologically homologous structural arrangements. Inter-specific overlaps in vessel distribution, growth ring boundaries, and axial parenchyma geometric layouts will inevitably increase marginal confusion errors. Resolving this requires shifting from standard global feature extractors to multi-scale network approaches (such as WoodGLNet) or attention mechanisms designed to capture localized microscopic diagnostic variations while discarding macro-structural noise [11].
- **Class Imbalance in Tropical Datasets:** Second, as evidenced by our SAF national data audit, real-world timber extraction is intensely concentrated in a small group of dominant taxa, creating a severe statistical disparity compared to low-volume or endangered conservation priorities [15]. Translating this raw reality into a training repository inherently creates a massive class imbalance. If left unmitigated, convolutional networks will develop a majority-class bias, artificially inflating global accuracy while exhibiting catastrophic recall drops for rare species. To prevent this, the future expansion framework must decouple raw commercial availability from dataset structure by enforcing a rigid target baseline of 1000 images per class, supplemented by specialized loss functions (such as Focal Loss or class-weighted cross-entropy) during the training pipeline to penalize misclassifications of underrepresented taxa.
- **Edge Computing and Computational Constraints:** Third, expanding the taxonomic catalog directly impacts the model's parameter density and memory footprint. High-capacity architectures evaluated on servers (such as EfficientNet-B7) handle high dimensionality with ease but are computationally unfeasible for decentralized field monitoring. To ensure the expanded 35-class model remains operational as a native Edge AI tool on mainstream mobile devices, the network optimization pipeline must implement severe structural compression. This process relies on post-training integer quantization (converting float32 weights to int8) to shrink the model into lightweight TensorFlow Lite formats (.tflite). This mathematical compression is vital to maintain an inference latency below the operational threshold of 200 ms on low-end ARM processors without exhausting the limited RAM available to field enforcement officers in disconnected environments [3,10].

4.6. Limitations of the Study and Future Outlook

Although the integrated technological framework demonstrated high technical robustness and operational readiness, several inherent limitations must be explicitly addressed to guide future expansions.

- **Taxonomic Scope:** First, the computer vision classification system evaluated during this initial Pilot Phase I was restricted to five commercially critical and threatened Neotropical forest species. While this selective target allowed for high precision, expanding the model to the planned 35 commercial taxa will introduce complex analytical challenges related to the high dimensionality of the feature space and morphological overlaps within taxonomically close groups.

- **Sample and Dataset Size:** Second, although the current database relies on a robust standard of 400 original macroscopic images per species sourced from independent physical wood blocks to prevent data leakage, deep learning generalizability inherently increases with dataset scale. Scaling up to a consolidated repository of 1000 images per species is a mandatory requirement to ensure the model remains resilient against anatomical variations caused by age, growth rates, and ecological site conditions.
- **Geographic Validation Scope:** Third, the field validation and operational latency testing of the 'Wood Identifier UTN' app were geographically circumscribed to commercial sawmills and timber yards in the urban and peripheral areas of Ibarra, Imbabura province. While Ibarra represents a strategic logging transit crossroad between the Andean highlands and the Pacific lowlands, these localized test environments do not capture the full spectrum of environmental noise, extreme humidity, or variable field illumination typical of deep forest control checkpoints across other megadiverse Ecuadorian regions.

Future iterations of the project will directly address these constraints by conducting multi-regional field trials across the Amazon and coastal provinces, fine-tuning hyperparameters for multi-class edge architectures, and opening data transfers to global reference networks like InsideWood and World Forest ID.

4.7. Multidisciplinary Forensic Integration for Advanced Timber Traceability

To establish an unassailable, multi-layered forest governance framework, decentralized edge-computing computer vision must not operate in isolation; instead, it should serve as the high-throughput screening node within a broader, multidisciplinary forensic ecosystem. In tropical forest law enforcement, field-deployed tools like the 'Wood Identifier UTN' app provide an immediate, low-cost diagnostic capability that effectively flags structural anomalies or potential mislabeling at primary transit checkpoints. However, when legal disputes arise or absolute standards-of-proof are required for judicial prosecution, this macroscopic computer vision approach can be seamlessly synchronized with advanced analytical methodologies, including DNA barcoding, stable isotope ratio analysis (SIRA), and mass spectrometry [25,26].

- **DNA Barcoding Synergy:** While macroscopic cellular patterns differentiate wood species based on structural features, genetic tools provide high taxonomic resolution capable of discriminating between closely related species or even identifying specific populations [21]. Integrating the LAMX physical baseline with DNA extraction protocols enables double-blind verification: the AI application performs a rapid, non-destructive taxonomic filtering in field depots, while anomalies or high-value timber lots can be sampled for molecular sequencing to confirm botanical authenticity at the genotype level.
- **Stable Isotope Ratio Analysis (SIRA) for Provenance Verification:** One of the main limitations of computer vision is its inability to verify geographic provenance, as wood anatomical structures remain relatively uniform across regional populations of the same species. Stable isotope analysis (leveraging spatial variations in $\delta^{18}\text{O}$, $\delta^2\text{H}$ and $\delta^{13}\text{C}$ ratios derived from local precipitation and soil chemistry) effectively maps the exact geographic origin of timber products. By cross-referencing SAF transport permits with SIRA baselines, environmental authorities can detect laundering schemes where wood harvested from protected conservation areas is falsely declared as originating from authorized management plans [24].
- **Mass Spectrometry (DART-TOFMS):** Furthermore, rapid chemical profiling via Direct Analysis in Real Time Time-of-Flight Mass Spectrometry (DART-TOFMS) can

complement wood anatomy by identifying species-specific metabolomic fingerprints in minutes [27]. The integration of these distinct technical scales creates a robust forensic pipeline: edge-computing AI acts as the widespread, cost-effective first-response tool for on-site rangers, while mass spectrometry, isotopes, and genomics provide the centralized, rigorous validation required to withstand legal cross-examinations in court. This holistic approach bridges the gap between field-level monitoring and advanced laboratory forensics, providing Ecuador with a transformative mechanism to combat the illegal timber trade.

5. Conclusions

This study presents the first peer-reviewed, comprehensive characterization of the LAMX wood collection at the Technical University of the North in Ecuador, documenting a strategic repository of 510 cataloged wood samples belonging to 56 families, 106 genera, and 127 species, complemented by an archive of 2267 histological preparations. The collection successfully integrates institutional specimens, transfers from PROAMAZONÍA, and direct links with herbarium vouchers, consolidating a solid scientific reference infrastructure for the forensic identification of wood in the country.

The audit analysis of the SAF data allowed for the structuring of a prioritized list of 129 commercially valuable timber species, revealing patterns of intense extraction pressure on key taxa and identifying critical gaps both in the national digital monitoring system and in the laboratory's own physical collection. This information will inform the planning of future targeted forest collection campaigns.

The integration of the macroscopic image database with the “Wood Identifier UTN” mobile application demonstrated the technical and operational feasibility of AI-assisted botanical identification under real-world field conditions. Using the lightweight MobileNetV2 architecture optimized for edge computing (Edge AI), the system achieved an overall accuracy of 94.04% and an F1 score of 0.976. Furthermore, the incorporation of Explainable AI techniques using Grad-CAM scientifically validated that the model bases its predictions on actual xylotomic diagnostic characteristics (vessels, rays, and parenchyma), ensuring the transparency and repeatability of the process.

Looking ahead to the project, the following recommendations are made:

Prioritize expanding the physical wood collection to incorporate high-volume extraction taxa that currently represent collection gaps at LAMX.

Consolidate the deployment of Phase II by expanding the AI model to 35 commercial timber species, starting from the structured repository of 1000 images per species.

Progressively incorporate multiscale network approaches (such as WoodGLNet) and openly transfer validated anatomical data to international reference platforms such as InsideWood and World Forest ID.

Evaluate, in the medium term, the integration of complementary technologies (such as DNA barcoding and stable isotopes) to strengthen the diagnosis of geographic provenance.

In conclusion, this integrated methodological framework establishes an adaptable, low-cost, and scientifically rigorous model for the forensic identification of wood that can be successfully replicated in other Neotropical regions facing similar challenges in forest governance, biodiversity conservation, and combating the illegal trafficking of timber resources.

Supplementary Materials: The following additional information can be downloaded from: Zenodo <https://doi.org/10.5281/zenodo.20359585>, Table S1 A-B-C: Complete catalog of wood collections (plates; test tubes; families and genera). Table S2: Complete list of prioritized species. Table S3: CNN model performance metrics. Evaluation indicators such as accuracy, recall, and F1 score are

presented for each class, obtained from the validation set, in order to analyze the model's performance for each species. The confusion matrix is shown, demonstrating high performance in classifying the evaluated species, with overall F1-score values of 0.973, accuracy of 0.976, and recall of 0.972. Most predictions are concentrated on the main diagonal, indicating accurate classification with minimal errors between morphologically similar classes. It is worth noting that the "Zoo" class does not correspond to a forest species but rather represents images outside the target class set, included to improve the model's ability to differentiate samples not belonging to the training set. Images S4: Image database of 5 species with 1000 photographs. Application executable code S5. APK file for use on Android mobile devices.

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