CaragaITreePier: A Mobile Application for Wood Identification Using Deep Learning

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Abstract

The wood industry is vibrant in Mindanao, and particularly in the Caraga Region. Industrial tree plantation (ITP) has become a solution to declining forest cover, as the extraction of wood from natural forests was gradually regulated until eventually banned in 2010. Identification of the wood of ITP species is a valuable process. From a traditional method of identifying wood and preventing fraud during timber trading, the authors envisioned a modern approach that is accurate and hassle-free by integrating knowledge in forestry and the advancement of technology. Therefore, CaragaITreePier-a mobile-based application that uses deep learning algorithm-was developed for the wood identification of priority ITP species in the region. With this application, ordinary people can now perform proper wood identification by simply scanning the wood using macrolens attached to a cellphone. The results of the application evaluation showed a high precision in the classification of wood samples. In terms of performance efficiency, the mobile application provided users a smooth experience in loading, predicting, and displaying information. Finally, the overall evaluation of the user respondents further confirmed that CaragaITreePier is user-friendly and a promising tool for the classification and authentication of wood species. The fundamental concept of the system is a trained artificial intelligence model with deep learning capabilities that can match human-level accuracy while using computing power for wood identification. Moreover, the advantage of the system is its portability, as CaragaITreePier can be used on mobile phones anywhere even without internet connectivity.

Keywords: Convolutional Neural Network, CaragaITreePier, deep-learning, industrial tree plantations, wood identification application.

1. Introduction

The ITP (Industrial Tree Plantation) wood identification process in Mindanao is valuable, especially in Caraga Region being dubbed the “Timber corridor of the Philippines’ for being the country's leading timber producer. ITP has become a solution for the current decrease in forest cover. Reforestation using ITP species has been a potential mechanism to restore the cover of Philippine forests [1].

The integration of forestry and technology has paved the way for technological advancement, leading to the development of wood identification applications on Android mobile devices. With this device, wood identification has become an innovative process compared to the traditional identification of wood species using magnification lenses, microscopes and stereoscopes [2]. Additionally, lumber trading companies, buyers, and sellers can ensure that their wood products are genuine.

The classification of images using neural networks is an output of digital technologies because it has been enhanced with deep learning, most often involving convolutional neural networks (CNN), in which the images are trained to identify the species with their structural features [3]–[8].

In this study, we designed and developed a mobile application using deep learning for the identification of 12 species in the Caraga region, using TensorFlow to identify wood species through image classification. The output would greatly benefit the wood industry sector and DENR following Executive Order No. 23, which declares a moratorium on the cutting and harvesting of timber in natural and residual forests and creates an anti-illegal logging task force (FAO, 2011).

As a prototype application with a limited database, only the following ITP species were included: *Acacia mangium*, *Aquilaria malaccensis*, *Endospermum peltatum*, *Eucalyptus deglupta*, *Falcataria moluccana*, *Gmelina arborea*, *Gymnostoma rumphianum*, *Melia azedarach*, *Polyscias nodosa*, *Shorea contorta*, *Shorea negrosensis*, *Swietenia macrophylla*, and *Toona calantas.*

2. Materials and Methods

Materials

Software

The proponents used Python as their programming language because of its readability and compatibility with libraries, making machine learning operations more efficient. However, the proponents only used Python to preprocess the datasets to be fed into the neural network. For mobile application development, the JavaScript programming language was used, along with a mobile development framework called React Native. The final building of the mobile application is executed using Expo, a tool that makes it easy to build applications that run on both the Android and IOS platforms.

Similarly, TensorFlow was used to save the trained model from Google's Teachable Machine (a web-based tool used to train models). TensorFlow.js was used to integrate the model into the application.

Hardware

The units used in the project development included a desktop computer with an Intel® CoreTM i5-4460 CPU @ 3.20GHz with 8 GB of 2400 MHz DDR3 and NVIDIA GeForce GTX 960 GPU, a cell phone with an Octa-core (4x2.2 GHz Kryo 260 Gold & 4x1.8 GHz Kryo 260 Silver) CPU, Adreno 512 GPU, 64 GB storage, and 6GB RAM.

Data

The researchers manually collected the data sets by capturing images of wood samples from college wood collections. For each wood sample, 100 sample images were collected using a digital microscopic lens extended to a phone device via the Camera Fi2 application. The application allows video recording using a smartphone or USB camera. Figure 3 shows the sample image data used to train the neural networks.

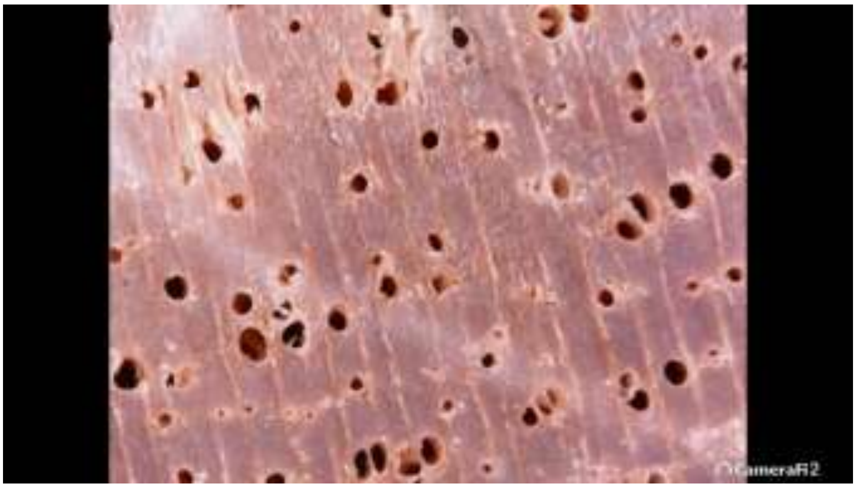

Figure 1. Sample of image data captured

3. Algorithm Implementation

Standard Convolution

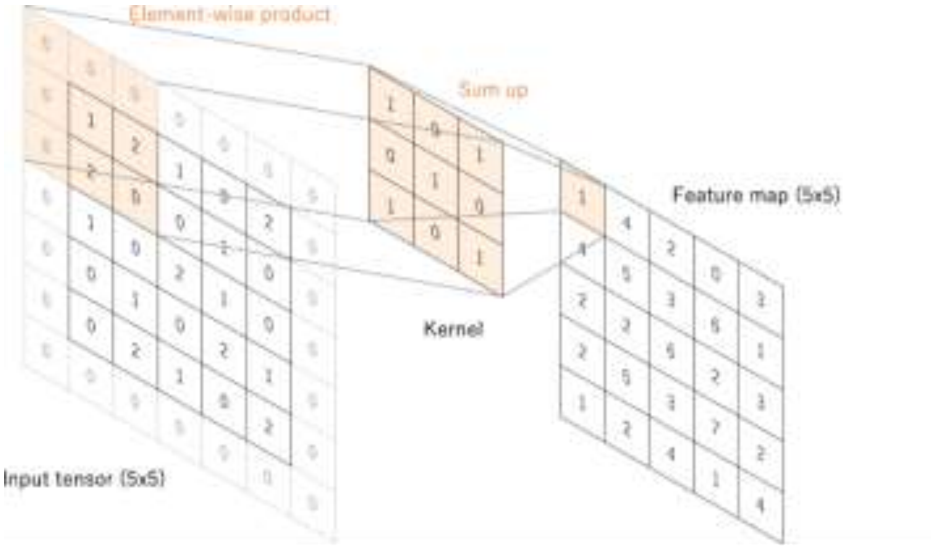

Figure 4. Convolutional Neural Networks

The network shown in Figure 4 is the most often used for image recognition and analysis. Multilayered artificial neural networks provide accurate results for image processing and object detection [9], [10]. The sliding of one matrix over another perfectly describes the mathematics of convolutions. Earlier studies took advantage of CNN to identify patterns in images because of its hidden or convolutional layers called kernel, which is commonly two-dimensional and works as a filter that extracts features from the original image. The sliding of the kernel to the input data is called a shift-compute procedure, which can be performed in two ways: noncausal or causal convolutions.

A recent study on tree species identification [11] used a convolutional neural network from bark images. The focus of their study was to apply a deep learning algorithm to identify trees species during the navigation of drones for autonomous forest management. However, the study was limited to classifying trees using cameras that can only see the barks of the woods - the same level as the human naked eye - as opposed to this study that focuses on the anatomy of the wood that is not easily visible in human eye.

Depthwise Convolutions

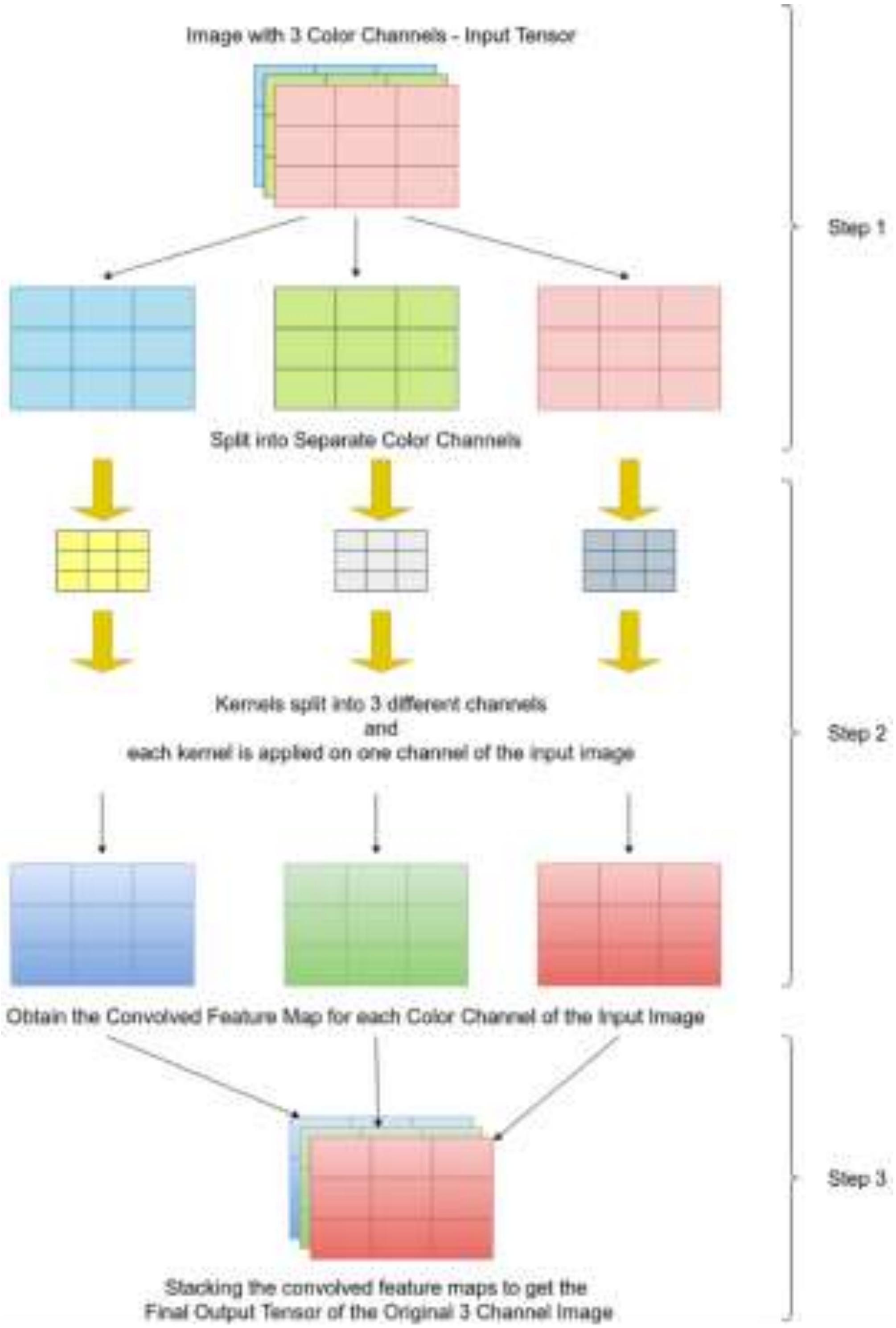

Figure 5. Depthwise Convolution

Figure 5 shows the depthwise convolution process. The main difference between standard 2D convolution and depthwise convolution is that standard convolutions are performed over all input channels, while in depthwise convolution, each channel is kept separate. This approach involves splitting the input tensor of three dimensions into separate channels. In each channel, the input feature was convolved with a 2D filter. The output of each channel is then stacked to merge the outputs of the entire 3D tensor.

Depthwise Separable Convolutions

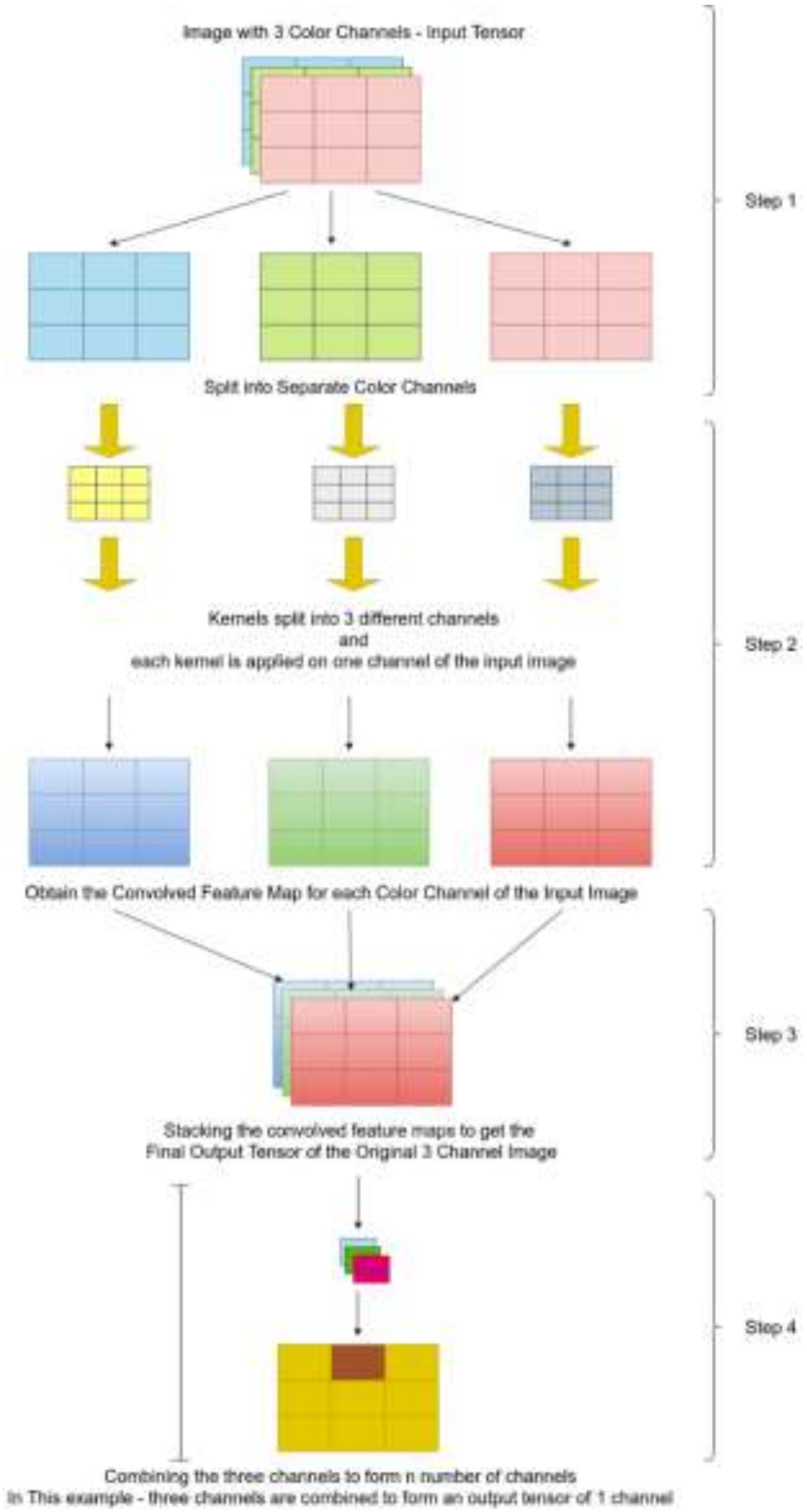

Figure 6. Depthwise Separable Convolutions

As shown in Figure 6, depthwise separable convolutions [3] are generally the result of applying depthwise convolution along with another step. This step consists of two parts: the filtering step and the combination of output channels into a single output channel. Hence, the process begins with splitting the input tensor into separate channels. Subsequently, a corresponding kernel per channel was convolved, resulting in a feature map for each channel and stacking to combine the results and form the number of channels.

Project development

This study focused on the design and development of CaragaITreePier, a mobile application that classifies digital microscopic images of woods belonging to 12 ITP species in the Caraga region. The researcher developed a mobile application by following the waterfall method.

Planning and gathering of requirements

During this phase, the researchers planned the goals and scope of the study. Decisions such as the selection of the deep learning model, features of the application, and limitations of the study are discussed in this section. Initially, a feature in which the user can capture an image directly from the application was included. However, this feature requires extensive knowledge of the software development. Therefore, we decided to use an external mobile application that uses a USB-connected external digital microscopic camera.

Data Gathering

Before deciding which 'wood' samples were included in the study, the researchers first verified the availability of each species and then collected them. For instance, the *G. rumphianum* was obtained from Carrascal, Surigao del Sur, *G. arborea* and *F. moluccana* were obtained from Claver, Surigao del Norte, and the remaining wood samples were borrowed from the wood collections of the College of Forestry and Environmental Sciences. The researchers began capturing 100 images of each sample using a digital microscope for a clearer view of the wood pores and then connected them to a cell phone using Camera FI2.

Data Storage and Pre-processing

The collected data set was stored on Google Drive and the local repositories. The next step was pre-processing.

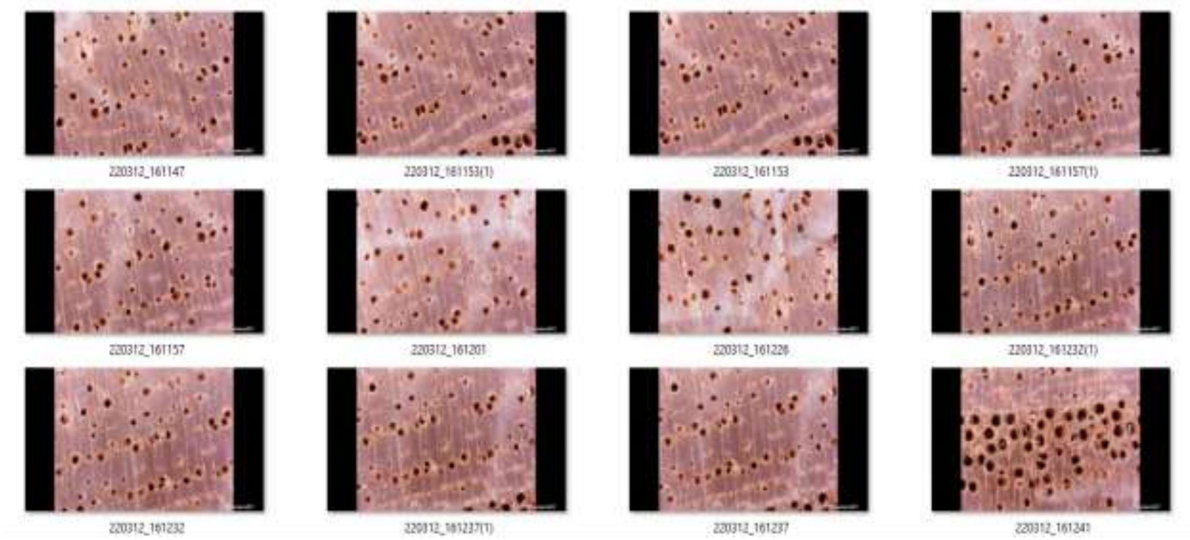

Figure 9. Digital microscopic images of *M. azedarach*.

As shown in Figure 9, the images collected using a USB-connected external digital microscopic camera and the external mobile application Camera Fi2 had thick borders on both the left and right sides. Because they were not biologically part of the wood anatomy, researchers had to remove the borders using a cropping method.

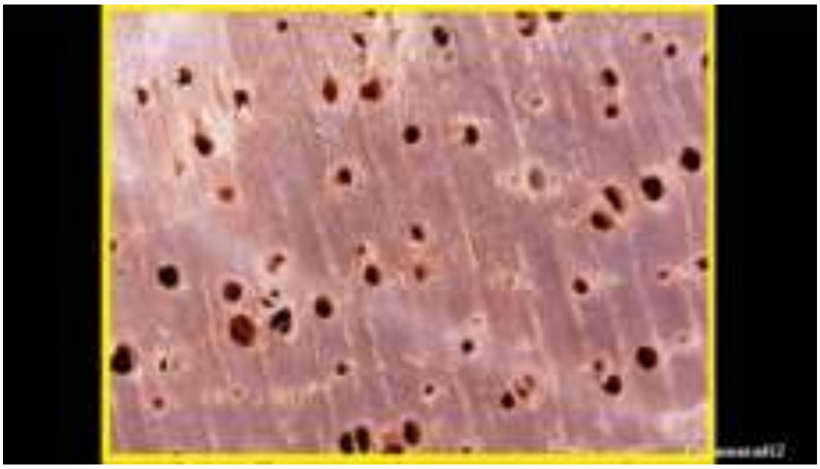

Figure 10. The cropped part of the image on the box dimension

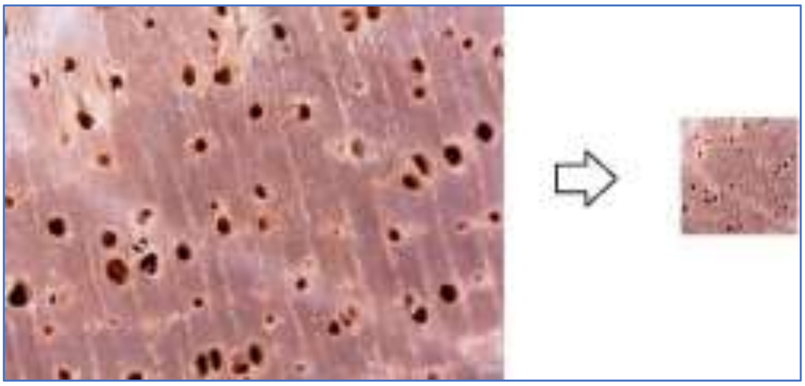

Figure 11. The image size was reduced to a smaller size.

Python programming was used to automate image cropping because manually cropping the images would result in inaccurate image dimensions. Additionally, manual cropping of images would require a considerable amount of time because the researchers gathered 100 images per tree species out of 12, making 1200 images.

Design

In this phase, the researchers determined the programming language, tools, and frameworks to be used to satisfy the features and requirements. The first step is to select the model. As mentioned in Section 3, the MobileNet neural network architecture was used as a model for image classification. Therefore, the proponents used an already existing machine learning platform. Google's Teachable Machine. React Native was also used to develop the mobile application because of the availability of tutorials on YouTube.

Implementation

The researchers created their machine learning model, based on MobileNet, on Google's Teachable Machine website. Before exploring the actual use of the Teachable Machine website, they read the manuals and tutorials available online to guide them in the creation of the model. Subsequently, they went ahead to access the machine-learning platform.

Upon using the platform, the researchers selected a standard image model with 224 × 224-pixel images as input. As mentioned earlier, proponents have already preprocessed their images to the required dimensions. Moreover, the researchers' dataset was composed of colored images; hence, instead of choosing the embedded image model, the standard image model was the inevitable choice.

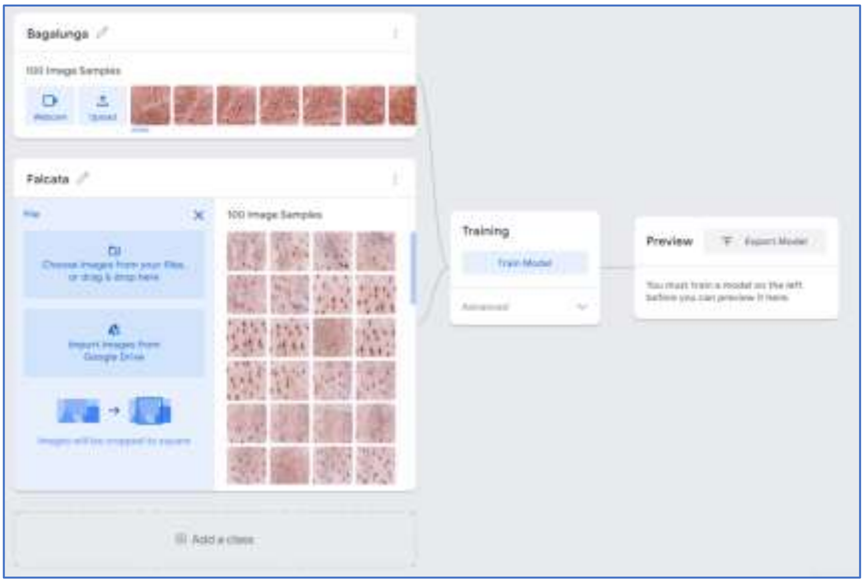

Figure 12. Loading of the dataset per tree species

The next process involves loading the images from the local storage. The word '*class'* can be referred to as the type of tree species. Therefore, adding a class means adding tree species to the wood sample images. Once all the classes were loaded, the model was ready for training.

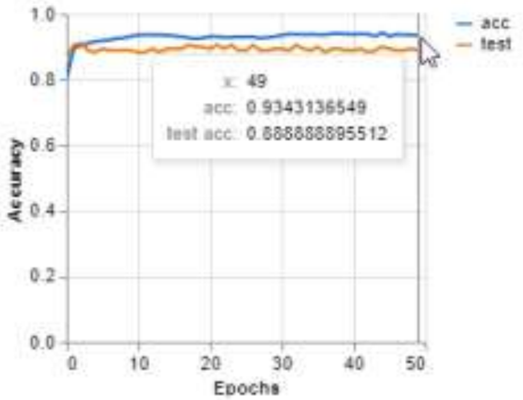

Figure 13. Accuracy of the Model

After 50 epochs, the model achieved an accuracy of 93.43% and testing accuracy of 88.89%. The training results suggest that the model is valid and ready to use. Hence, the next step was to download the model and use it in TensorFlow.js.

With the model ready, researchers began developing a mobile application using the React Native and Expo. Developing a mobile application using Expo makes it easier for researchers to build the entire application owing to its built-in tools. The trained model was integrated during the application development.

Project Evaluation

This section addresses the evaluation techniques used by the proponents to obtain the necessary feedback and responses from the chosen evaluators. This section includes discussions of the evaluators, standards, and survey forms used.

Researchers selected respondents included students, faculty members, and industrial plantation practitioners with knowledge of forestry or basic wood identification. The survey instrument includes basic questions about operation experience with the developed mobile application. Table 1 lists the basic operational parameters to be assessed, and the data will be analyzed using the index set in Table 2.

Table 1. Mobile Application Evaluation statements.

Evaluation Parameters	5	4	3	2	1
Functional Suitability					
The application provided me with the correct prediction.					
All the features present in the application are functioning correctly					
Performance Efficiency					
The application runs smoothly (Loads fast)					
The application provides predictions in a short time.					
Satisfaction					
The application's ability to predict might be helpful for me in the future					
The application is fool-proof and easy to navigate.					

Table 2. Likert Scale Interpretation

Rating	Scale	Interpretation
5	4.20 – 5.00	Strongly Agree
4	3.40 – 4.19	Agree
3	2.60 – 3.39	Slightly Agree
2	1.80 – 2.59	Disagree
1	1.00 – 1.79	Strongly Disagree

4. Results and Discussions

Project Description/Structure

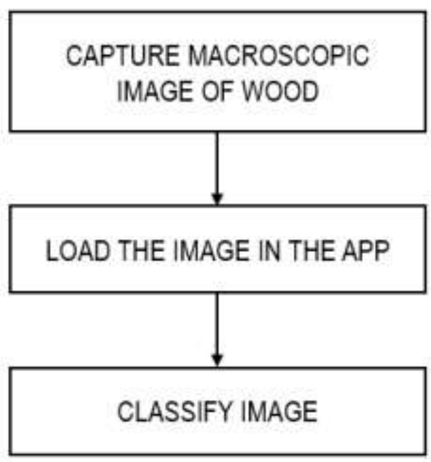

Figure 14. The straightforward flow of the mobile application.

This section explains the flow of information between the user and the system developed in this study. Figure 14 presents a general overview of this application. As mentioned above, the first step for the user to use the application is to capture a digital microscopic image of the wood sample.

Figure 15. Homepage

Figure 15 shows the 'Homepage' of the application. On this page, the user selects an image using the *SELECT IMAGE* button. Users can also opt to go to other pages, such as details and pages, using the navigation buttons at the bottom of the screen.

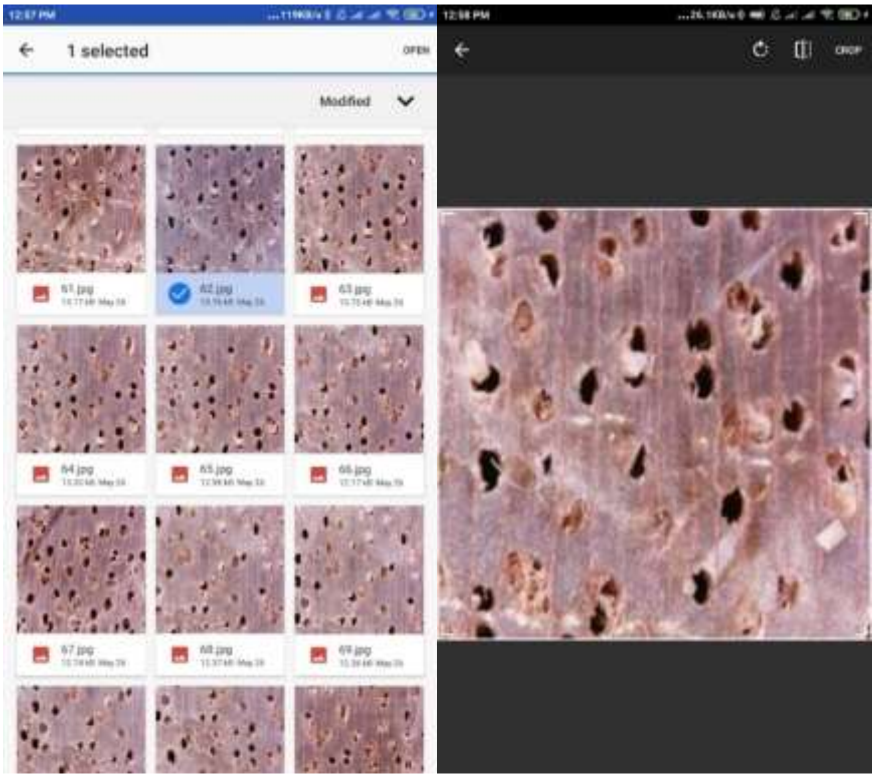

Figure 16. Image selection (*left*) and cropping (*right*).

This prompts users to freely choose a microscopic image from wood. Once an image is selected, another prompt is displayed asking the user to select a part (cropped) of the image. Cropping is necessary so that the image to be classified contains only meaningful data from the wood anatomy.

Figure 17. Results of the prediction (*left*) and detail page (*right*).

After the selection of the image, the result of the prediction is shown as a percentage in Figure 17. The details of the prediction, such as the percentage form of the probability and the details of the tree species, are displayed. The details of the wood samples are displayed, including their name, scientific name, family name, topography, number, size, tyloses, deposits, type, parenchyma, and rays.

Project Limitations/Capabilities

In the classification and identification of wood species, the application proved to accurately classify the images of wood samples and shown in a range of probability percentage as displayed. However, due to limited data storage as a prototype, **t**he mobile application was only able to classify and identify woods from the 12 ITP species, as discussed in this study. Currently, mobile applications only allow image loading where users must take a picture using a digital microscopic camera that can be run using an external application called Camera Fi2.

Project Evaluation

Researchers used a five-point Likert scale to evaluate mobile applications. The ISO 25010 software quality factors, such as functional suitability, performance efficiency, and satisfaction, were the basis for this evaluation. The evaluation with technical and non-technical respondents was conducted via Google Forms, which can only be accessed with a logged-in Google account and only accepts one entry per email where the Data Privacy Policy was seen.

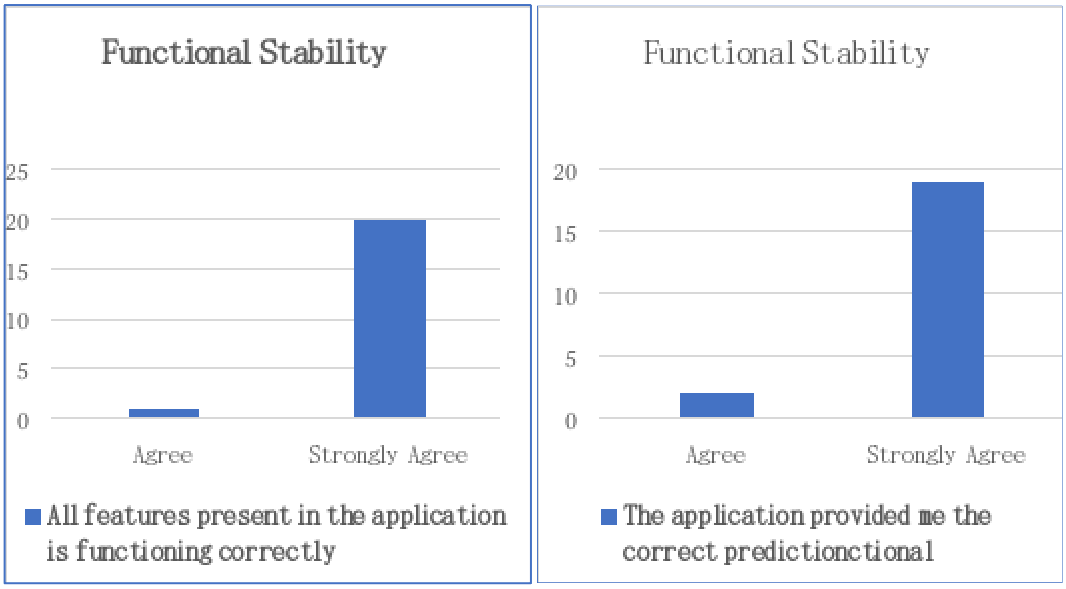

Figure 18. Responses about the functional suitability of the application.

As shown in Figure 18, the mobile application received positive responses from users about its ability to provide accurate predictions. The user responses are shown in Figure 18 (a), and they strongly agree that the classification of the model is accurate. Similarly, in Figure 18 (b), the users strongly agree that the applications have worked correctly throughout their use.

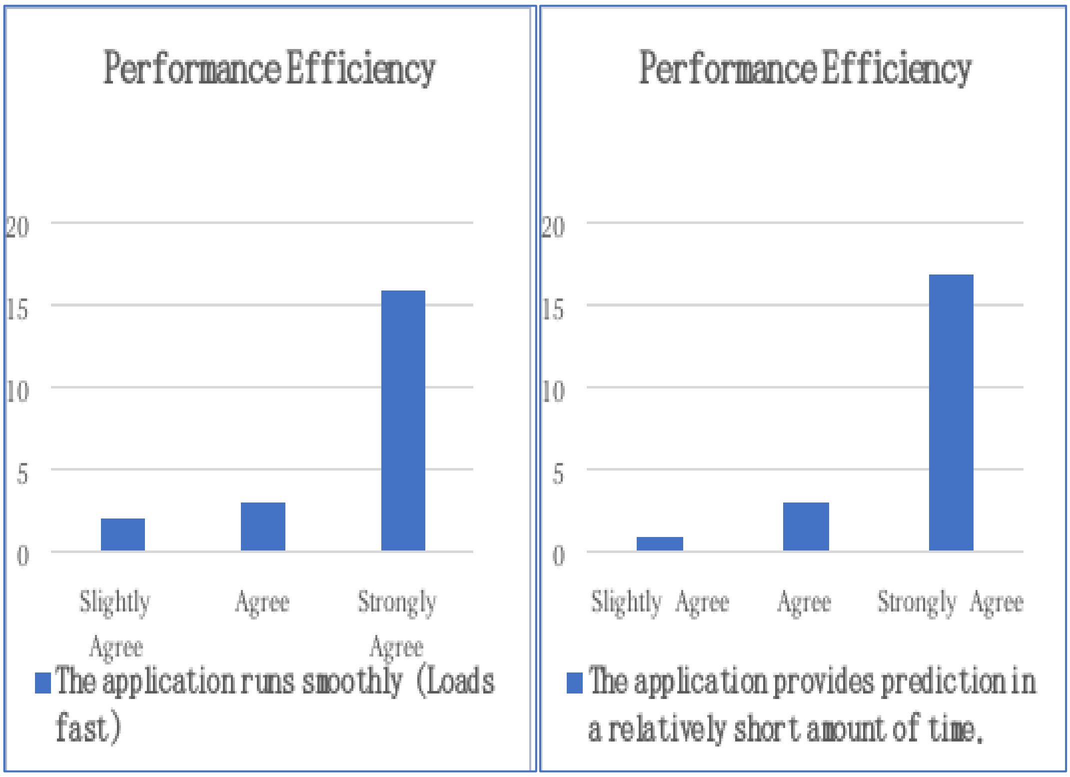

Figure 19. Responses to performance efficiency.

As shown in Figure 19, the mobile application received positive responses from the users about its smooth functionality. The user responses are shown in Figure 19 (a), where the user is most strongly agrees that the mobile application runs and loads quickly. Similarly, as shown in Figure 19 (b), most users strongly agreed that the applications were relatively fast in determining the wood species.

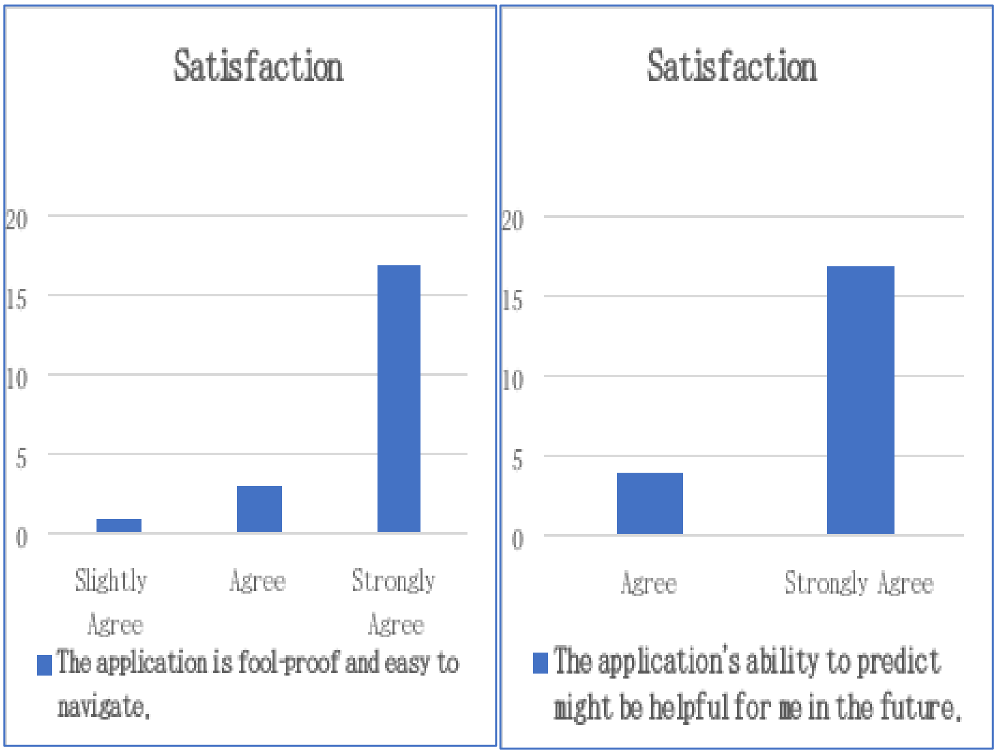

Figure 20. Responses about satisfaction.

Figure 20 shows that the mobile application also gathered positive responses from users regarding their helpfulness. The users' responses are shown in Figure 20(a), where most strongly agreed that the mobile application might be helpful for them in the future. Similarly, as shown in Figure 20(b), most users strongly agreed that the application is easy to use.

Table 4. Summary of the evaluation

Category	Mean Score
Functional Suitability	4.88
Performance Efficiency	4.72
Satisfaction	4.79
Overall Score	**4.80**

Table 4 summarizes the evaluations conducted. Regarding functional suitability, most evaluators strongly agreed that the mobile application supplied the correct prediction or classification and that the features of the mobile application functioned correctly. Moreover, the result in terms of performance efficiency shows that the mobile application runs smoothly on its device and that the prediction only takes a short amount of time.

Furthermore, the satisfaction results indicated that most of the evaluators strongly agreed that the product might be helpful in the future and that the application would be easy to use and navigate. The evaluation resulted in an overall score of 4.80, indicating that the development of the mobile device application was successful.

5. Conclusions

The researchers designed and developed a mobile application that classified 12 ITP species in the Caraga region. The model used in the application was trained using the data collected by the researchers. Researchers have been able to export and integrate this model into mobile applications. Moreover, the application does not directly classify the tree species but also provides meaningful details, such as the percentage probability of the image belonging to a tree species, along with the tree species information. The application itself is a helpful tool for authenticating wood, as it supplies a probability percentage that can be used as a gauge to check the authenticity of the wood.

The results of the evaluation suggest that the mobile device application, in terms of functional suitability, performed very well, as it could accurately classify and function correctly upon use. Furthermore, in terms of performance efficiency, the mobile application could provide users with a smooth experience as it loaded, predicted, and displayed information quickly. The evaluation results further confirmed that CaragaITreePier is easy to use and is a promising tool for the classification and authentication of tree species.

However, the application model achieved an accuracy of approximately 93.43%. This implies that there is room for improvement. There are several ways in which an application model can be improved by increasing the volume of the dataset. However, in this study, due to limited resources in time, the researcher settled on a relatively decent volume of data sets to develop an application as a proof of concept.

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