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Anatomy Identification of Bamboo Stems with The Convolutional Neural Networks (CNN) Method

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Abstract

Bamboo is important to note that some species of bamboo are protected and considered endangered. However, distinguishing between traded and protected bamboo species or differentiating between bamboo species for various purposes is still a challenge. This requires specialized skills to identify the type of bamboo, and currently, the process can only be carried out in the forest for bamboo that is still in clump form by experienced researchers or officers. However, a study has been conducted to develop an easier and quicker method for identifying bamboo species. The study aims to create an automatic identification system for bamboo stems based on their anatomical structure (ASINABU). The bamboo identification algorithm was developed using macroscopic images of cross-sectioned bamboo stems, and the research method used was the Convolutional Neural Network (CNN). The CNN was designed to identify bamboo species with images taken using a cellphone camera equipped with a lens. The final product is an automatic identification application on Android, which can accurately detect bamboo species with an accuracy of 99.9%.

Keywords: *asinabu; convolutional neural network; identify bamboo; macroscopic images*

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1. Introduction

Bamboo, a member of the *Poaceae* family, is known for its fast growth and unique characteristics. [1]. Bamboo is a highly versatile plant that can be used for various applications, such as biofuel, food, construction, and architecture. It plays a critical role in the local economy by providing job opportunities. This remarkable plant has distinct and rapid growth patterns and can help protect the environment from pollution while enhancing soil quality [2]. The bamboo stem is composed of vascular bundles and parenchyma ground tissue. The stem's properties are determined by the size, shape, arrangement, and number of the vascular bundles [3]. Bamboos are a fast-growing group of woody grass species, widely distributed across tropical and sub-tropical regions of the world, and are an important species of the Indian subcontinent [4]. Throughout history, bamboo has been widely used in Japan for structural purposes and crafting tools such as fishing rods, due to its exceptional structural properties. While composite materials have become increasingly popular in recent years, the traditional design of the slim, tapered, hollow cylindrical fishing rod has remained unchanged throughout the centuries of fishing [5]. Bamboo treated with Tung oil not only improves its hydrophobic property and dimensional stability but also its resistance to fungal attack and mechanical performance. [6]. Light is one of the most adverse factors for bamboo deterioration and causes surface degradation and discolouration [7]. Bamboo Timber (BT) is a kind of natural porous material, and usually, bamboo cracking and deformation are caused by the change of humidity in the environment. Inspired by the natural structure of the shell, a multilayer structure was designed to fabricate a kind of graphene/silica composite coating on the BT surface [8]. Bamboo has a hierarchical, anisotropic structure that affects its physical and mechanical properties through moisture transport due to its hygroscopic nature. [9]. The plant

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microbiota plays a crucial role in Moso bamboo's productivity, nutrient uptake, stress resistance, and flowering. The mechanism of flowering is connected to nutrient uptake, temperature, hormone balance, and the regulation of key genes. [10]. To enhance bamboo performance and increase its value, we investigate the effects of impregnation and thermal treatment on its structure. [11]. Design for poverty alleviation (DPA) is an increasingly popular practice of rural social innovation. It selects traditional Chinese handicrafts, such as Shengzhou bamboo weaving, to discuss the key elements of sustainability, including the roles, benefits, and interactions of multiple actors involved. [12]. An existing residential building designed by architect Anna Zanetti has been rebuilt in Bologna, a municipality in northern Italy. The new construction site uses Moso (*Phyllostachys* edulis), a structural material cultivated in Italy, replacing Guadua angustifolia and Dendrocalamus asper which were used in the original building located in Costa Rica. [13].

Stems are made up of various types of cells and can therefore be studied as cellular solids. In addition, the stem can be viewed as a composite structure on multiple scales, with sclerenchyma fibres embedded within the parenchyma cell matrix. The fibres themselves are also a composite, made up of multiple layers of cellulose fibrils. [14]. Nutrient-storing parenchyma cells wrap around bamboo fibres in their natural tissue structure. [15]. Stem sheaths lack bulliform cells or trichomes in their epidermis, and their elongated shape resembles branches.[16].

The program uses machine learning techniques to identify different bamboo species. The accuracy level of the program depends on the classification of the bamboo species. Machine learning is a field that deals with data analysis through various statistical tools and learning processes, which helps to extract more knowledge from the data. [17]. Since 1996, machine learning has been widely used due to its time efficiency, accuracy, and lack of need to fulfil classical assumptions of traditional methods. However, machine learning models primarily process stored data. [18].

With the continuous increase in computing power, image classification technology is rapidly evolving. This growth is mainly due to the existence of deep learning, which significantly improves the accuracy of object recognition. Deep learning allows computational models to study data representations with different levels of abstraction, thanks to the multiple processing layers. Deep convolutional nets have made significant strides in processing images, videos, speech, and audio, while iterative nets have shown their effectiveness in handling sequential data, such as text and speech [19]. To identify or classify an object in an image, we use a pattern that defines and describes it. This pattern is known as a drawing pattern class, which is a group of sample objects that share common characteristics such as their geometry, texture, and mathematical descriptions. Image pattern recognition involves analyzing and evaluating various forms of material data and graphic information. It helps to classify, evaluate, and illustrate images for a specific purpose or entity, such as a political organization.[20].

Neural Networks undertake a comparative analysis between several different available supervised algorithms to identify one best-suited neural architecture that can work best in the applied fields [21]. The advantages of using Convolutional Neural Networks (CNN) for image analysis have been applied to various research cases, including image classification, object detection, and semantic image segmentation. Additionally, CNN has strong capabilities that can automatically learn high-level feature representations from images and extract features for image classification. Three-dimensional Convolutional Neural Networks (3D-CNN) models were used to develop and validate the automatic segmentation of core segments in images [22]. Furthermore, Class Activation Mapping was used to identify discriminatory image regions used by CNN [23]. An improved deep convolutional neural network (CNN) with batch normalization and MSRA (Microsoft Research Asia) initialization is proposed to discriminate the tobacco cultivation regions using data collected from the NIR sensor. [24] The identification of bamboo stem anatomy has never before utilized Convolutional Neural Networks (CNN). Three different CNN architectures were implemented: ResNet50, ResNet101, and DenseNet201. The third architecture is responsible for reading patterns in macroscopic images of bamboo and comparing them with existing photos in the database. This comparison leads to a classification of ten types of bamboo, including Andong, Ampel, Apus, Ater, Betung, Duri, Manggong, Maya, Tutul, and Wulung. We then optimize using Adam and evaluate the results using F1-score, Precision, Recall, and accuracy. Afterwards, we developed an anatomy application for bamboo stems and tested it using Blackbox testing. [25].

The process of segmenting masses in pancreatic ductal adenocarcinoma and identifying surrounding blood vessels on CT images involved the use of a Convolutional Neural Network (CNN) alongside classical features. The first step involved localizing the pancreatic region using the 3D Local Binary Pattern (LBP) map of the original image, which was achieved by utilizing the 3D-CNN architecture. [26] Imaging techniques have a wide range of applications in geosciences. Scanning Electron Microscopy (SEM) and micro-CT scanning are commonly used to study various geological problems. Despite notable improvements in imaging capabilities and image processing algorithms, obtaining high-quality data from images remains a challenging and time-consuming task. [27]

During the research, the team examined woods such as cedar, cypress, Korean pine, Korean red pine, and larch. They aimed to develop an automatic wood species identification system using a CNN model with macroscopic images captured from smartphones. This method was chosen to facilitate the identification process. Any smartphone used for research purposes must have a camera, as well as sufficient lighting. However, lighting proved to be a challenge during the study. To overcome this obstacle, the team used artificial neural network techniques, which provided a solution to the limitations of conventional feature extraction methods that require high-quality images captured under controlled lighting. It is crucial to research the various types of bamboo to classify and categorize them. Each type of bamboo possesses unique characteristics, such as flexibility, strength, and usefulness, which makes it imperative to know their types. This knowledge can be utilized in bamboo laboratories. However, the current conventional method of identifying a bamboo type involves a time-consuming process of taking it to the laboratory, which is not effective.

This study aims to create a computational Convolutional Neural Network (CNN) that can accurately and swiftly differentiate between various bamboo species based on their anatomical characteristics. Presently, the lack of information technology and a shortage of skilled personnel impede the bamboo identification process, causing delays and limited capacity. The proficiency and speed of the process rely on the knowledge and experience of the researchers or officers involved.

The research conducted was successful in creating a model that can identify the anatomy of bamboo stems. This was achieved using the Convolutional Neural Networks algorithm, with three architectures - ResNet50, ResNet101V2, and DenseNet201. The testing of the algorithm on these three architectures revealed that ResNet50, with an input network size of 224, was the best model. The ASINABU application that was developed as a result of this research can detect bamboo species with an accuracy of 99,9%.

2. Research Methods

The research was carried out in several stages, namely data collection, data preprocessing, model creation, evaluation, model testing, application creation, and application testing. The flow of research stages consists of the initial stage with collecting internode images. This image is used to preprocess data consisting of training data, validation data, and test data. The model is built with training data and validation data, while test data is used for evaluation. Testing is carried out to find out whether the prediction is correct or not, if not, the model must be revised until the prediction results are correct.

2.1. Materials

The study involved the use of both hardware and software components. The hardware included a computer, a smartphone, a loupe, a cutter, bamboo, and a whiteboard marker. In terms of software, we utilized the Android operating system, Android Studio, Convolutional Neural Networks (CNN), ResNet50, ResNet101V2, DenseNet201, Library keras, Python program, and Google Colab facilities throughout the entire study phase. The hardware specifications included a GPU Memory of 16 GB, GPU clock of 2.5 GHz, CPU Dual Core, RAM of 16 GB, and Disk Space of 200 GB. The smartphones used are the Samsung Galaxy S9 and the Xiaomi Readmi 10 5G. The Samsung Galaxy S9 has a 12 MP front camera with an f/1.5-2.4 wide lens, while the Xiaomi Readmi 10 5G sports a 50 MP front camera with an f/1.8 wide lens. In addition, the loupe used is a 50X zoom Mini Glass Magnifier Glass with LED light, which is a microscope and loop magnifying glass combined.

2.2. Sample Preparation

The image data was obtained from old bamboo with internodes. The bamboo has varying sizes, and the image data captured is known as macroscopic image data. This type of data is considered primary data since it's collected directly from the source and can be seen using a magnifying tool with a magnification of 10-20 times. The bamboo species used in the data collection process is accurate as it comes from a validated authentic collection verified by researchers who used herbarium material. The data collected consists of 10 species of commercial bamboo that are commonly found in Indonesia.[28]:

Table 1. The name of bamboo

Name of bamboo	Scientific name
Andong	*Gigantochloa pseudoarundinaceae* (Steud) Widjaja
Ampel	*Bambusa vulgaris* Scharader ex Wendland
Apus	*Gigantochloa apus* (Schutz)
Ater	*Gigantochloa atter* (Hassk) Kurz ex Munro)
Betung	*Dendrocalamus asper* Backer
Duri	*Bambusa blumeana* J.A. & J.H. Schult
Manggong	*Gigantochloa manggong* Widjaya
Mayan	*Gigantochloa robusta* Kurz
Tutul	*Bambusa maculata* Widjaja
Wulung	*Gigantochloa atroviolacea* Widjaja)

2.3. Image Acquisition in Stem Internodes

To ensure ease of locating internodes, three random photos of internode type three were taken from bottom to top of the cross-section of bamboo sticks. This was done to highlight the fact that internodes are not only present on the bottom edge. However, due to the large amount of data involved, it requires significant storage capacity, lengthy data processing, and efficient algorithms for proper data analysis [29]. Bamboo stems cut horizontally display outer and inner layers, and all cross-sections are photographed during image collection. Figure 1 depicts an internode.

This image of the internode is converted into data that is used during testing. Three different CNN methods, namely ResNet50, ResNet101, and DenseNet201 architectures, are utilized to make predictions based on identical data for each test. However, it has been observed that the results of these predictions differ, even though the data used is the same. These prediction outcomes are then used as the basis for creating algorithm models for the Asinabu application.

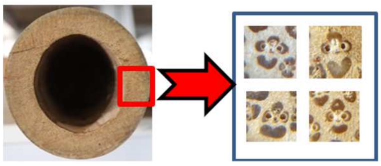


Figure 1. Image of Internode

2.4. Dataset

The dataset comprised 1000 images, with each image belonging to one of the ten different types of bamboo, namely Ampel, Andong, Apus, Ater, Betung, Duri, Mayan, Manggong, Tutul, and Wulung. Each type of bamboo had 100 images, which were further divided into 700 for training data, 200 for testing, and 100 for validation. Data preprocessing is an important step that involves data cleaning, integration, transformation, and reduction. These steps are crucial for data preparation, and if any one of them is missed, the data mining algorithm may produce unexpected results [30]. To simplify the process of comparing or matching classifications, feature extraction involves changing the image size from 3024 x 3024 pixels to 224 x 224 pixels, and converting the color to RGB (red, green, blue). Machine learning and deep learning can analyze the performance of learning methods for predictions using extensive data sets [31]. Image data processing typically comprises five main stages: data acquisition, data preprocessing, feature extraction and fusion, algorithm pattern classification, and applying the data. Once the image data is collected, the process starts with data input and validation. Next, the data is divided into training and validation datasets and then subjected to data augmentation using CNN-based deep learning structures. After that, the internode training process is carried out, followed by the final validation process. I obtained data from the Xylarium Bogoriense 1915 laboratory, which is located at Jalan Gunung Batu Number 5, Bogor. The data was gathered by capturing images of bamboo sticks using a cellphone camera and a loupe attachment that can magnify up to 60 times. The bamboo stems were identified by experts as a unique type of bamboo with distinct characteristics. The resulting photos are macroscopic images of the bamboo internodes. To capture these images, the bamboo was cut crosswise and the loupe was attached to the camera. This allowed for capturing an internal image that shows a distinctive pattern within the internode, which is then used as the basis for research on bamboo characteristics.

2.5. Research Stages

The research was conducted in five stages: data collection, data pre-processing, model development, model testing, and model evaluation and comparison. Figure 2 illustrates the flow of the research stages.

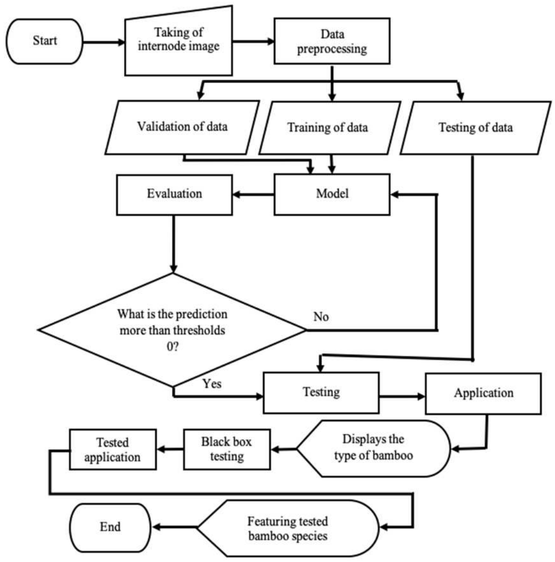


Figure 2. Flow Chart of Research Stages

2.6. Flow Research Work Model

In the context of water distribution networks (WDN), a Convolutional Neural Network (CNN) is used to predict pipe burst locations. To achieve optimal performance, the CNN is fine-tuned through a hyperparameter optimization process. This process involves tuning various parameters such as dataset size, normalization, batch size, learning rate regularization, model structure, and early stopping criteria. [32].

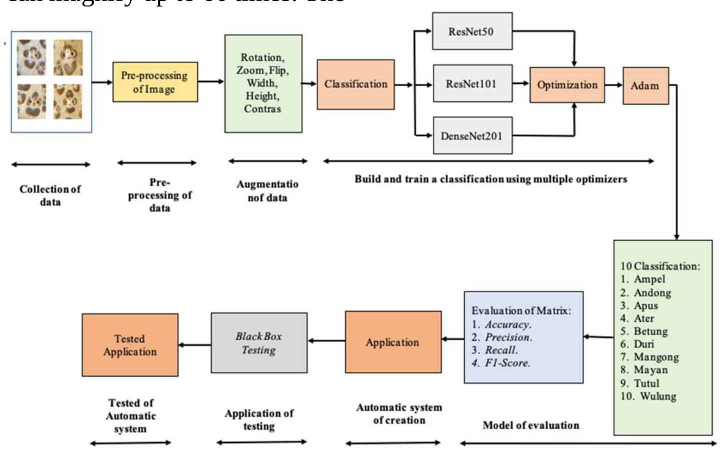


Figure 3. Flow Research of Working Model

Many real-world applications require optimization in dynamic environments, where the challenge is to locate and track the optima of a time-varying objective function [33]. The research work model followed a specific flow which included data collection, pre-processing and augmentation, building and training model classifications using various optimizers, evaluating the model, developing an automated system, and finally evaluating the applications. This process is illustrated in Figure 3.

2.7. Using of Models

The algorithm model design is applied to the input data layer of an image measuring 3024 x 3024 pixels in size. The image is then trimmed to a size of 224 x 224 pixels for each of the Red, Green, and Blue (RGB) colours. Various augmentations such as rotation, image enlargement, wide shift range, and horizontal flip are applied. The architecture used in this model includes ResNet50, ResNet101, and DenseNet201, which contain depth convolutional layers. Normalization is applied twice, with the ReLU layer used after the first normalization layer and the dense layer used after the second normalization layer. A dropout layer is then applied after the Dense layer, followed by a fully connected layer. The softmax layer is used after the fully connected layer to display the classification of bamboo types. Finally, a classification layer is used to provide the classification of the bamboo types.

2.7.1. Convolutional Neural Networks (CNN)

Convolutional Neural Networks are used in neural networks to recognize and classify images (CNN). Image recognition is used in a variety of applications [34]. CNN, or convolutional neural network, has recently emerged as a highly effective technique for designing porous structures. However, a CNN model typically consists of a large number of parameters, each of which can significantly affect the predictive ability of the model. Additionally, there is currently no consensus on the optimal settings for each parameter within the CNN model. [35]

An architecture algorithm, along with a Convolutional Neural Network (CNN), can accurately identify bamboo stem anatomy. The results of various architectures, including ResNet50, ResNet101, and DenseNet201, were compared to assess accuracy. Along with identifying anatomical features, the model can predict scientific classifications and identify image types. Model validation was used to compare predicted values to observed ones, resulting in high accuracy. The cellphone application is equipped with a model that can identify the anatomy of a bamboo stem using several parameters such as architecture, total parameters, epoch, batch, learning rate, callbacks, and augmentation. The augmentation process includes rotation rate, width shift range, height shift range, and horizontal flip on the model.

The CNN input parameters are analyzed, including the number of convolutional layers, the number of filters in each layer, the size of the convolution kernel, and the activation function. The impact of these parameters on the accuracy of classification and the time required to train the network is assessed. [36]. In this application scenario, non-essential experimental parameters should be excluded based on the model design rules and actual experimental results. [37]. Figure 4 is an illustration of the Convolutional Neural Networks (CNN) model.

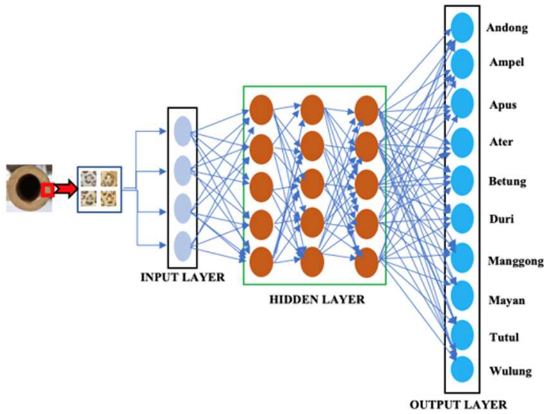


Figure 4. Convolutional Neural Networks (CNN)

The models were trained using the Adam optimizer and categorical cross-entropy loss function, with the activation function being sigmoid, moreover, the transfer learning model was pre-trained on ImageNet to ensure high accuracy with various datasets. Froze the pre-trained layers and retrain only the fully connected layers. All model setups were configured identically to facilitate the analysis of performance. [38]. The model parameter used for this research is presented in Table 2.

Table 2. Model parameters

Parameters	Value
Epoch	200
Batch Size	64
Input Shape	244 x 244 x 3
Optimizer	Adam
Augmentation	Rotation, Zoom, Flip, Width, Height, Contras.
Pooling	Flatten layer
Activation	ReLU
Dropout rate	0.5
Loss Function	Categorical cross entropy
Weights	ImageNet

2.7.2. ResNet50

The ResNet50 network consists of six main parts: the input module, four blocks numbered 3, 4, 6, and 3 in each module, and the output module. The basic building block of this network model is a residual block structure. ReLU activation functions are used at each level, and batch normalization units are added to improve the adaptability of the model. The ADAM optimizer is selected to improve the accuracy of network recognition. The dimensional parameters of each block of the ResNet50 network and the two-dimensional output dimensions of each block are shown in Table 3 [39].

Table 3. Architecture resnet50

Layer name	Net	Output
Conv1	7 x 7, 64, stride2	112 x 112
Conv2_x	3 x 3 max pool, stide2 $\begin{bmatrix} 1x1 & , & 64 \\ 3x3 & , & 64 \\ 1x1 & , & 64 \end{bmatrix}$ x 3	56 x 56
Conv3_x	$\begin{bmatrix} 1x1 & , & 128 \\ 3x3 & , & 128 \\ 1x1 & , & 512 \end{bmatrix}$ x 4	28 x 28
Conv4_x	$\begin{bmatrix} 1x1 & , & 256 \\ 3x3 & , & 256 \\ 1x1 & , & 1024 \end{bmatrix}$ x 6	14 x 14
Conv5_x	$\begin{bmatrix} 1x1 & , & 512 \\ 3x3 & , & 512 \\ 1x1 & , & 2048 \end{bmatrix}$ x 6	7 x 7
Average pool, 1000-d fc, Softmax		1 x 1

For this study, an algorithm model was designed as shown in Figure 5. The model includes the following components: data input, image size training, augmentation, convolutional layer, normalization layer, ReLU layer, dense layer, dropout layer, fully connected layer, softmax layer, and classification layer.

Figure 6 shows the number of epochs of 200 with accuracy parameters with one architecture is ResNet50. An epoch is a data set used to train a convolutional neural network and coincides with the full set of input data. One data set consists of 700 training, 200 testing and 100 validation.

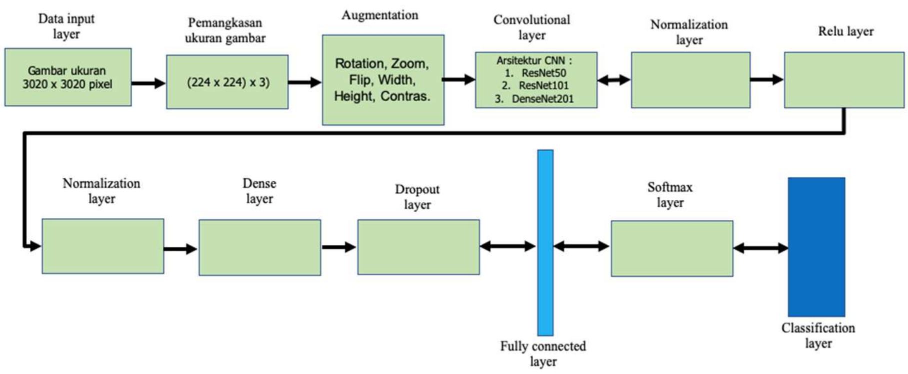


Figure 5. Model of Algorithm Design

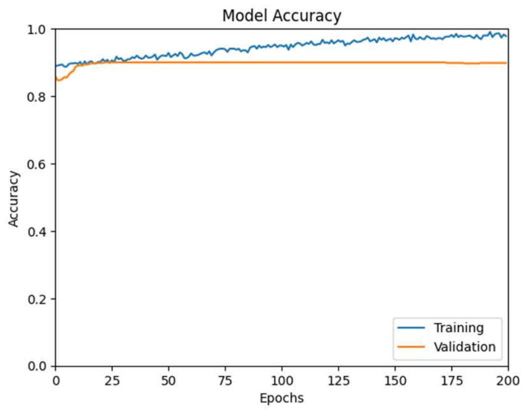


Figure 6. Model Accuracy ResNet50

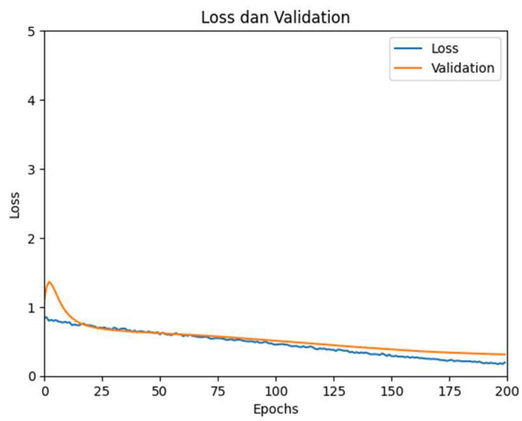


Figure 7. Model Loss ResNet50

2.8. Evaluation

Model evaluation is carried out based on performance evaluation metrics that occur from accuracy, precision, recall, and f1-score, as a performance evaluation matrix used for model evaluation [40]. In addition, the final evaluation was carried out using black-box testing to measure the correctness of the application. The formula used for the performance of the basic confusion matrix mentioned above as evaluation criteria: Accuracy = (TP+TN)/(TP+FP+FN+TN). Recall = (TP) / (TP + FN). Precision = (TP) / (TP+FP). F1 Score = 2 * (Recall*Precision) / (Recall + Precision). Information: TP=True Positive. FP=False Positive. FN=False Negative. TN=True Negative.

The result of the evaluation with precision, recall, f1-score, and accuracy, parameters on models with the ResNet50, ResNet101, and DenseNet201 architecture are presented in Table 4.

2.9. Testing

Model testing for the identification of bamboo stem anatomy was carried out on bamboo images in the Xylarium Bogoriense laboratory, at the Center for Standardization of Sustainable Forest Management Instruments with a total of 1000 images, and an image size of 3024 x 3024 pixels and the image was trimmed to 224 x 224 pixels.

Table 4. The evaluation of the model

Architecture	Accuracy	Precision	Recall	F1 Score
ResNet50	0,90	0,93	0,95	0,94
ResNet101	0,81	0,91	0,86	0,89
DenseNet201	0,88	0,91	0,95	0,93

2.10. Black Box Testing

Black box testing is a testing technique that involves examining the fundamental aspects of an application without any knowledge of its internal workings. This approach has little or no relevance to the internal logical structure of the system. [41]. The method utilized the Gradient Boosting Classifier method for black box testing. This method combines multiple parameters to create a powerful parameter that is included in a set of machine learning algorithms, resulting in predictions as output. It is a widely favoured method due to its effective classification of data sets. The Gradient Boosting Classifier was tested using the parameters of estimators, max features, max depth, and criteria. The resulting values are presented in Table 5.

Table 5. Result of black box testing

Architecture	Value
ResNet50	0,75

3. Results and Discussions

The testing identification of bamboo stem anatomy using the Convolutional Neural Networks (CNN) algorithm with ResNet50, ResNet101, and DenseNet201 architectures with an input size network scenario of 224. The model testing results are shown in Table 6. After the model is created, visualization of the confusion matrix model plot needs to be done to determine the value of the model as in Figure 8.

Table 6. The results testing of confusion matrix

Architecture	Loss	Time detection (scond)	True positives	False positives	True negatives	False negatives
ResNet50	0,310	9,6	1,0	2,0	574	63,0
ResNet101	0,355	12	0,0	3,0	573	64,0
DenseNet201	0,314	5,6	3,0	1,0	575	61,0

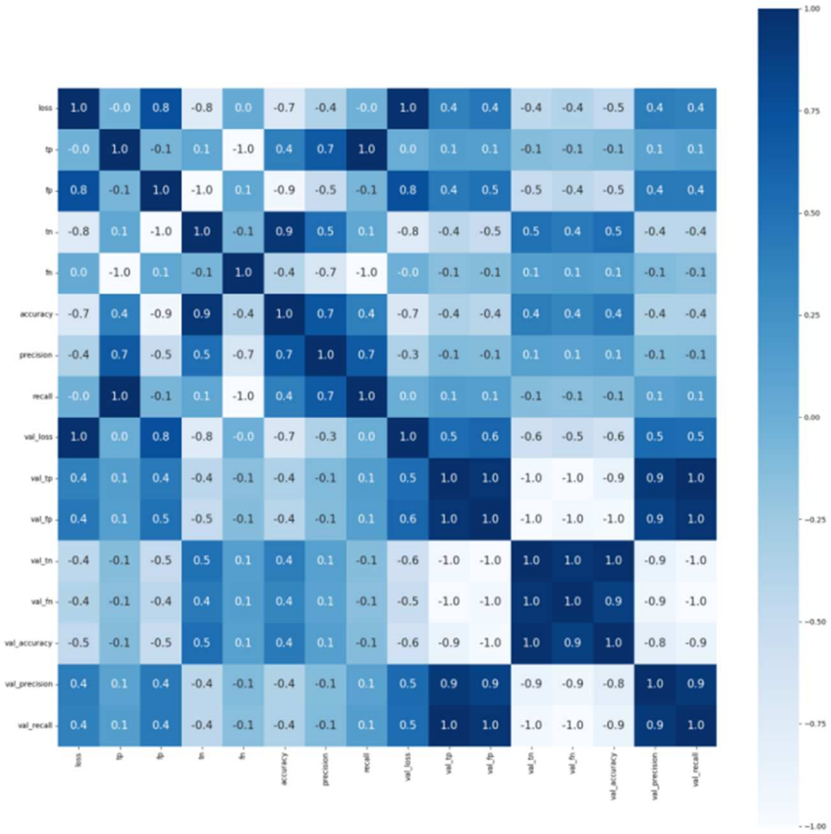


Figure 8. Visualization of The Confusion Matrix Model Plot With The ResNet50 Architecture

The test results show that the ResNet50 value has the best value, 90% accuracy, the lowest loss value, 0.310, and a detection time of 9.6 seconds/1000 images. The ResNet101 value has the best value, 81% accuracy, the lowest loss value, 0.355, and a detection time of 12 seconds/1000 images. The DenseNet201 value has the best value, 88% accuracy, the lowest loss value, 0.314, and a detection time of 5.6 seconds/1000 images. After testing the best model for use in the application of identification of bamboo stem anatomy is ResNet50 because it has better accuracy than ResNet101 and DenseNet201.

3.1. Prediction Results

The Convolutional Neural Networks (CNN) algorithm was used to train and validate data using ResNet50, ResNet101, and DenseNet201 architectures with an input size network scenario of 224. Table 5 presents the best value for testing bamboo that was registered with the Xylarium Bogoriense 1915 laboratory.

Table 7 the results of testing the algorithm using the Convolutional Neural Networks method with architectures ResNet50. The test detected 1000 image objects with 10 different classes and showed good results on one architecture, however, the best results were found in models using the ResNet50 architecture.

The precision, recall, and f1-score metrics are all above 90%, indicating that the algorithm is good at identifying the anatomy of bamboo stems. The highest value was achieved by the ResNet50 architecture model, achieving a value of 0.9 or 90% accuracy.

Table 7. Prediction true or faulty

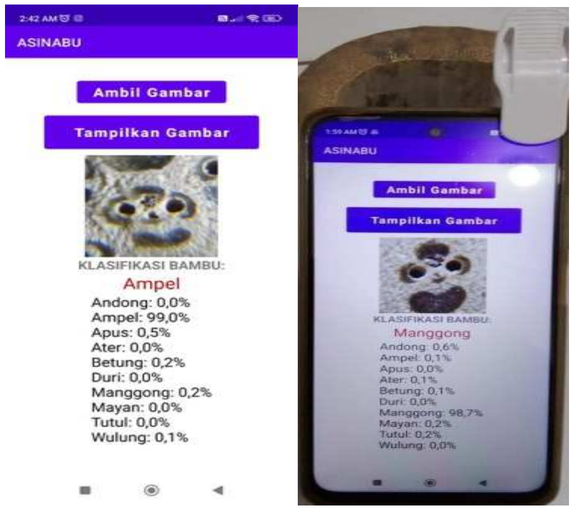
Bamboo of name	Prediction True or Faulty		Architecture
	True	Faulty	ResNet50
Ampel	Yes	-	0,99
Andong	Yes	-	0,99
Apus	Yes	-	0,99
Ater	Yes	-	0,99
Betung	Yes	-	0,99
Duri	Yes	-	0,99
Manggong	Yes	-	0,99
Mayan	Yes	-	0,99
Tutul	Yes	-	0,97
Wulung	Yes	-	0,99
	Average amount		0,97

The best loss value was achieved by the ResNet50 architecture model with a value of 0.310. The ResNet101 architecture model reached 0.355, while the DenseNet201 architecture model reached 0.314. It also had the best time detection value at 5.6 seconds, ResNet50 followed by at 9.6 seconds and ResNet101 at 12 seconds.

The researchers concluded from the results of the training and testing and determined the best input size network model for each of the algorithms based on various criteria, not just the f1-score value. Pattern precision is important because the bamboo internode pattern is used to make predictions in one image file. Prediction the model ResNet50 achieved an accuracy of over 0.97 or 0.97%. The correctness of the bamboo name prediction by the model was declared correct.

The black box testing of the three architectures, ResNet50, was valuable, with a value of 0.75, which is the highest after testing with the Gradient Boosting Classifier. The parameters Gradient Boosting Classifier used were estimators, max features, max depth, and criteria.

ASINABU is an application designed for the anatomical identification of bamboo stems. Upon testing the ASINABU application, it was found that the detected bamboo was of the Ampel type with an accuracy of up to 99%. This application can be installed on a smartphone with the Android operating system and serves as an internode detector. In conclusion, the ASINABU application can detect bamboo Andong species with an accuracy rate of 99.9%. After conducting research and applying Asinabu, the results resemble the print screen and Figures 9 and 10.



(a) (b)

Figure 9. Bamboo Stem Anatomy Identification Print Screen Detects. (a) Ampel Type of Bamboo Accuracy 99,0%, (b) Manggong Bamboo Type Accuracy 98,7% on The *Handphone*. The Model Does Not Mean There Is No Loss.

Figure 10. Asinabu Photo detects Andong bamboo with 99.9% accuracy on the Xiaomi Redmi 5G cellphone

4. Conclusions

The application of bamboo stem anatomy required the best model which turned out to be the one that achieved a total parameter of 49,724,874 and an accuracy rate of 0.90 or 90%. The third model used ResNet50, ResNet101, and DenseNet201 architectures and achieved an evaluation where accuracy, precision, recall and f1 score values show the highest in the ResNet50 architectural model with an accuracy value of 0.90 or 90%, precision of 0.93 or 93%, recall of 0.95 or 0.95 and f1 score of 0.94 or 94%. ASINABU application can detect bamboo Andong species with an accuracy rate of 99.9%.

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References

[1] S. Dutta, A. Deb, P. Biswas, S. Chakraborty, S. Guha, D. Mitra, M. Das, B. Geist, A. R. Schaffner, "Identification and functional characterization of two bamboo FD gene homologs having contrasting effects on shoot growth and flowering," *Scientific Reports,* (11):7849, 2021, doi.org/10.1038/s41598-021-87491-6

[2] A. Emamverdian, Y. Ding, F. Ranaei, Z. Ahmad, "Application of bamboo plants in nine aspects," *The Scientific World Journal*, 7284203, 2020, doi: 10.1155/2020/7284203.

[3] A. Darwis, A. H. Iswanto, "Morphological characteristics of Bambusa vulgaris and the distribution and shape of vascular bundles there," *Journal of the Korean Wood Science and Technology*, 46(4):315-322, 2018, doi:10.5658/WOOD.2018.46.4.315

[4] S. Sngh, H. Singh, S. K. Sharma, and R. Nautial, "Seasonal variation in biochemical responses of bamboo clones in the sub-tropical climate of Indian Himalayan foothills," *Heliyon*, 7, e06859, 2021, doi:10.1016/j.heliyon.2021.e06859

[5] R. Nishiyama, and M. Sato," Structural rationalities of tapered hollow cylindrical beams and their use in Japanese traditional bamboo fishing rods," Scientific Reports 12:2448, 2022, doi:10.1038/s41598-022-06426-x

[6] T. Tang, X. Liu, B. Fei, B. Zhang, X. Chen, W. Wang, "Synergistic effects of tung oil and heat treatment on physicochemical properties of bamboo materials," *Scientific Reports,* (9):12824, 2019, doi.org/10.1038/s41598-019-49240-8

[7] H. Yu, S. He, W. Zhang, M. Zhan, X. Z, J. Wang, and W. Yu, "Discoloration and degradation of bunder ultraviolet radiation," *Hindawi International Journal of Polymer Science,* Volume 2021, Article ID 6803100, 10 pages, doi: 10.1155/2021/6803100

[8] J. Wang, Y. Zhou, J. Li, Y. Feng, J. Zhang, H. Yu, and X. Zhuang, "Improved wettability and dimensional stability of bamboo timber by coating graphene/silica composites, " Improved wettability and dimensional stability of bamboo timber by coating graphene/silica composites," *Hindawi International Journal of Polymer Science*, Volume 2021, Article ID 7053143, 10 pages, doi:10.1155/2021/7053143

[9] Q. Chen, C. Fang, G. Wang, X. Ma, J. Luo, M. Chen, C. Dai and B. Fei, " Water vapor sorption behavior of bamboo pertaining to its hierarchical structure," *Scientific Reports* 11:12714, 2021, doi:10.1038/s41598-021-92103-4

[10] Z. S. Yuan, F. Liu, Z. Y. Liu, Q. L. Huang, G. F. Zhang, and H. Pan, " Structural variability and differentiation of niches in the rhizosphere and endosphere bacterial microbiome of mosobamboo (*Phyllostachys* edulis)," *Scientific Reports*, 11:1574, 2021, doi:10.1038/s41598-021-80971-9

[11] J. Gao, L. Qu, J. Qian, Z. Wang, Y. Li, S. Yi, and Z. He, " Effects of combined acid-alkali and heat treatment on the physiochemical structure of moso bamboo," *Scientific Reports* 10:6760, 2020, doi:10.1038/s41598-020-63907-7

[12] W. Li, Z. Li, and H. Kou, " Design for poverty alleviation and craft revitalization in rural China from an actor-network perspective: the case of bamboo-weaving in Shengzhou," *Heritage Science,* 10:2, 2020, doi:10.1186/s40494-021-00637-7

[13] G. Donini, S. Greco, L. Molari, and A. Zanetti," Structural design of an Italian bamboo house in an Italian regulatory context: Revisiting a small building built in Costa Rica with tropical bamboo," Elsevier, 2214-5095, 2022. doi: 10.1016/j.cscm.2022.e00891

[14] D. U. Shah, T. P. S. Reynolds, and M. H. Ramage, "The strength of plants: theory and experimental methods to measure the mechanical properties of stems," *Journal of Experimental Botany*, 68(16):4497-4516, 2017, doi: 10.1093/jxb/erx245.

[15] Q. Lin Q, Y. Lu, S. Liu, Y. Yu, Y. Huang, W. Yu, R. Gao, and D. Li, Bamboo-inspired cell-scale assembly for energy device applications. *NPJ Flexible Electronics*, (6):13, 2022, doi:10.1038/s41528-022-00148-w

[16] S. Wang, "Bamboo sheath-a modifed branch based on the anatomical observations," *Scientific Reports,* (7):16132, 2017, doi:10.1038/s41598-017-16470-7

[17] A. Faruk, E. S. Cahyono, N. Eliyati, and I. Arifieni, 'Prediction and classification of low birth weight data using machine learning techni," *Indonesian Journal of Science & Technology,* 3 (1) (2018) 18-28, 2018, doi:10.17509/ijost.v3i1.10799

[18] R. E. Caraka, R. C. Chen, H. Yasin, Suhartono, Y. Lee, B. Pardamean, "Hybrid vector autoregression feedforward neural network with genetic algorithm model for forecasting space-time pollution data," *Indonesian Journal of Science & Technology*, 6(1):243-266, 2021, doi: 10.17509/ijost.v6i1.32732

[19] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, (521):436–444, 2015, doi:10.1038/nature14539

[20] O. A. Paranjay and Rajeshkumar, " A neural network aided real-time hospital recommendation system," *Indonesian Journal of Science & Technology*, Volume 5 Issue 2, September Hal 217-235, 2020, doi.org/10.17509/ijost.v5i2.24585

[21] X. Zhang, "Application of artificial intelligence recognition technology in digital image processing," *Hindawi Wireless Communications and Mobile Computing,* 7442639(10), 2022, doi:10.1155/2022/7442639

[22] X. Han, X. Wu, S. Wang, L. Xu, H. Xu, D. Zheng, N. Yu, Y. Hong, Z. Yu, D. Yang, and Z. Yang, "Automated segmentation of liver segment on portal venous phase MR images using a 3D convolutional neural network," *Insights into Imaging*, (13):26, 2022, doi:10.1186/s13244-022-01163-1

[23] T. Majeed, R. Rashid, D. Ali, and A. Asaad, " Issues associated with deploying CNN transfer learning to detect COVID-19 from chest X-rays," *National Center For Biotechnology Information,* 43(4): 1289–1303, 2020, doi:10.1007/s13246-020-00934-8

[24] D. Wang, F. Tian, S. X. Yang, Z. Zhu, D, Jiang, and B. Cai, "Improved deep cnn with parameter initialization for data analysis of near-infrared spectroscopy sensors", *MPDI Sensor*, *20*(3), 874, 2020, doi:10.3390/s20030874

[25] T. S. Kang, B. J. Kim, K. Y. Nam, S. Lee, K. Kim, W. S. Lee, J. Kim, and Y, S. Han, "Asymmetry between right and left fundus images identifed using convolutional neural networks," *Scientific Reports,* (12):1444, 2022, doi.org/10.1038/s41598-021-04323-3

[26] T. Mahmoudi, Z. M. Kouzahkanan, A. M. Radmard, R. Kafieh, A. Salehnia, A. H. Davarpanah, H. Arabalibeik, and A. Ahmadian, "Segmentation of pancreatic ductal adenocarcinoma (PDAC) and surrounding vessels in CT images using deep convolutional neural networks and texture descriptors," *Scientific Reports,* 12:3092, 2022, doi:10.1038/s41598-022-07111-9

[27] M. Bizhani, O. H. Ardakani, and E. Little, "Reconstructing high fidelity digital rock images using deep convolutional

neural networks," *Scientific Reports*, 12:4264, 2022, doi:10.1038/s41598-022-08170-8

[28] O. Kwon, H. G. Lee, M. R. Lee MR, S. Jang, S. Y. Yang, S. Y. Park, I. G. Choi, and H. Yeo, "Automatic wood species identification of Korean softwood based on convolutional neural networks," *Journal of the Korean Wood Science and Technology*, 45(6):797-808, 2017, doi: 10.5658/WOOD.2017.45.6.797

[29] C. Firdaus, Wahyudin, and E. P. Nugroho, "Monitoring system with two central facilities protocol," *Indonesian Journal of Science and Technology*, *2*(1): 8-25, 2017, doi:10.17509/ijost.v2i1

[30] A. K. Srivastava, N. Safaei, S. Khahi, G. Lopez, W. Zeng, F. Ewert, T. Gaiser, and J. Rahimi, "Winter wheat yield prediction using convolutional neural networks from environmental and phenological data," *Scientific Reports,* (12):3215, 2022, doi:10.1038/s41598-022-06249-w

[31] A. Haryanto, T. W. Saputra, M. Telaumbanua, A. C. Gita, "Application of artificial neural network to predict biodiesel yield from waste oil transesterification," *Indonesia Journal of Science & Techonology*, (5):62-74, 2020, doi:10.17509/ijost.v5i1/2309

[32] A. Antunes, B. Ferreira, N. Marques, and N. Carrico, " Hyperparameter optimization of a convolutional neural network model for pipe burst location in water distribution networks," *Journal of Imaging*, 9, 68, 2023, doi:10.3390/jimaging9030068

[33] F. M. Talaat, and S. A. Gamel, " RL based hyper-parameters optimization algorithm (ROA) for convolutional neural network," *Journal of Ambient Intelligence and Humanized Computing*, 14:13349–13359, 2023, doi: doi:10.1007/s12652-022-03788-y

[34] A. Sehgal, H. La, S. Louis, and H. Nguyen, "Deep reinforcement learning using genetic algorithm for parameter optimization, " In: 2019 Third IEEE International Conference on Robotic Computing (IRC) (pp. 596–601), IEEE, 2019, doi:10.1109/IRC.2019.00121

[35] Y. Lu, Y. Huo, Z. Yang, Y. Niu, M. Zhao, S. Bosiakov, and L. Li, " Influence of the parameters of the convolutional neural network model in predicting the effective compressive modulus of porous structure," *Frontiers in Bioengineering and Biotechnology*, 10:985688, 2022, doi:10.3389/fbioe.2022.985688

[36] S. Maitra, R. K. Ojha, and K. Ghosh, " Impact of convolutional neural network input parameters on classification performance," *Institute of Electrical and Electronics Engineers*, 19514810, 2020, doi:10.1109/I2CT42659.2018.9058213

[37] Y. L. Liu, Y. K. Chen, W. X. Li, and Y. Zhang, " Model design and parameter optimization of CNN for side-channel cryptanalysis," *PeerJ Computer Science*, 8:e829, 2022, doi: 10.7717/peerj-cs.829

[38] M. Harahap, E. M. Laia, L. S. Sitanggang, M. Sinaga, and D. F. Sihombing, " Deteksi penyakit covid-19 pada citra x-ray dengan pendekatan convolutional neural network (CNN)," *Rekayasa Sistem dan Teknologi Informas*, Vol. 6 No. 1,70-77, 2022, doi:10.29207/resti.v6i1.3373

[39] I. Ahmad, M. Hamid, S. Yousaf, S. T. Shah, and M. O. Ahmad, "Optimizing pretrained convolutional neural networks for tomato leaf disease detection," *Hindawi Complexity*, Article ID 8812019, 2020, doi:10.1155/2020/8812019

[40] G. Wang, H. Yu, and Y. Sui, " Research on maize disease recognition method based on improved resnet50," *Hindawi Mobile Information Systems*, Article ID 9110866, 6 pages, 2021, doi:10.1155/2021/9110866

[41] B. Walters, S. O. Martorell, I. Olier, and P. G. J. Lisboa, "How to open a black box classifier for tabular data," *MPDI*: *Algorithms*, 16, 181, 2023, doi:10.3390/a16040181