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Coffee Rust Severity Analysis in Agroforestry Systems Using Deep Learning in Peruvian Tropical Ecosystems

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Abstract: Agroforestry systems can influence the occurrence and abundance of pests and diseases because integrating crops with trees or other vegetation can create diverse microclimates that may either enhance or inhibit their development. This study analyzes the severity of coffee rust in two agroforestry systems in the provinces of Jaén and San Ignacio in the department of Cajamarca (Peru). This research used a quantitative descriptive approach, and 319 photographs were collected with a professional camera during field trips. The photographs were segmented, classified and analyzed using the deep learning MobileNet and VGG16 transfer learning models with two methods for measuring rust severity from SENASA Peru and SENASICA Mexico. The results reported that grade 1 is the most prevalent rust severity according to the SENASA methodology (1 to 5% of the leaf affected) and SENASICA Mexico (0 to 2% of the leaf affected). Moreover, the proposed MobileNet model presented the best classification accuracy rate of 94% over 50 epochs. This research demonstrates the capacity of machine learning algorithms in disease diagnosis, which could be an alternative to help experts quantify the severity of coffee rust in coffee trees and broadens the field of research for future low-cost computational tools for disease recognition and classification

Keywords: agroforestry; disease assessment; coffee diseases; convolutional neural networks; AI in agriculture; deep learning

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1. Introduction

The main reason behind 80% of deforestation is the expansion of agriculture, which involves the clearing and burning of forests to expand agricultural areas, resulting in a change in land use that affects the ecological balance of the forest [1]. Strategies for adaptation to environmental change include the maintenance of shade trees in tropical agroforestry [2]. The restoration of tree cover through agroforestry can mitigate the negative effects of deforestation and complement ecosystem protection [3].

Agroforestry is a cultivation practice that associates one or more tree species with annual or perennial crops [4]. Its value lies in temporarily combining crops with trees or other vegetation to generate microclimates [5]. One of the main objectives of agroforestry systems is to nullify the harmful effects of monoculture, which is more susceptible to pests and diseases [6,7]. Pests and diseases cause severe crop losses, threaten agricultural production and reduce food security [8,9]. They also reduce economic income and threaten the livelihoods of thousands of families around the world, so pest and disease regulation as a benefit of agroforestry systems represents an important ecosystem service [10].

Coffee is traditionally grown under shade trees [11] and is considered one of the most important agroforestry crops in Latin America [12]. Given its importance, this crop has significantly modified the structure of rural landscapes in coffee growing regions [13]. Globally, an estimated 25 million rural farmers depend on coffee cultivation for their livelihood; most of them are small farmers with cultivated areas ranging from 1 to 5 ha [14]. In Peru, coffee is an important crop that is mainly grown in agroforestry systems; approximately two million families depend on its production, distribution and marketing [15,16]. It is produced in 210 rural districts located in 47 provinces in 10 regions of the country, with a cultivated area of 350,000 ha distributed in three zones, with the jungle being the most appropriate region to obtain the best yields and quality [17]. Peru is one of the main coffee exporters in the world, and coffee production is mainly driven by five regions: Cajamarca, Pasco, San Martin, Junin and Amazonas [18]. However, coffee production in recent years has been deeply affected by the high severity of coffee leaf rust [19].

Coffee is a crop at high risk from the effects of climate change [20]. Therefore, agroforestry practices have been proposed as a nature-based strategy for coffee farmers to mitigate and adapt to different future climate scenarios [21]. However, the resistance of coffee plants to foliar pests and diseases is also related to soil characteristics [20]. In fact, since the emergence of coffee pests and diseases, there have been two main control techniques: pesticide application and crop management techniques. In most cases, chemical control is almost ineffective and is associated with pesticide resistance, environmental contamination, chemical hazards and re-emergence [22].

Coffee leaf rust (CLR) is caused by the fungus *Hemileia vastatrix*, which infects leaves and causes premature leaf drop and severe defoliation and can also cause branch death [23,24]. Coffee leaf rust begins as small yellow powdery spots on the underside of the leaves [25]. Over time, they gradually increase in diameter and become orange lesions [26]. During severe rust infection, leaves become covered with pustules, which induces them to drop prematurely, reducing the photosynthetic area of the plant [27]. In South America, CLR was first identified in Brazil in 1970 and then spread to other countries [16]. In recent decades, the coffee sector has been under constant pressure from the spread of coffee rust in Latin America, which has directly affected the economic sustainability of smallholder households [28]. Major outbreaks of the disease in Asia, Africa and the Americas has caused severe yield losses, making it the most important disease affecting Arabica coffee [29]. Specifically, in the Americas, coffee rust epidemics have affected Colombia (2008–2011), Central America and Mexico (2012–2013), and Peru and Ecuador (2013) [16].

According to [30], in Peru, this disease caused epidemics between 2008 and 2013, with production losses of 35%. The cultivated area and production decreased between 2013 (429,000 ha and 252,800 tn) and 2014 (390,000 ha and 181,700 tn) [30,31]. Specifically, in 2013, during the so-called “rust crisis”, in the country, damage reached levels of economic importance, which translated into losses for the coffee sector of approximately 60% of the harvest, valued at about USD 290 M [32].

Although coffee rust was first reported in Peru in 1979, it did not cause substantial losses in coffee bean production until 2013, when the disease had the highest incidence [33]. Following this episode, the Peruvian government implemented a plan to renew coffee plantations; however, during the fourth quarter of 2014, the yellow rust disease caused a 14.7% reduction in production with respect to its long-term trend [34]. Because of this crisis, studies have shown that rust epidemics not only cause primary yield losses, i.e., in the current year [19,35], but also secondary yield losses, i.e., in the following years, due to the death of branches in the first year [28,35]. Other research considers coffee rust to be, for the coffee industry, potentially one of the causes of a sustainability crisis [19,36]. Its in situ detection is the only effective method for felling coffee trees to prevent infection. However, the accurate detection of infection over wide areas is difficult when performed by field surveys [37].

According to [38], the methods used to determine crop rust can be direct or indirect and destructive or nondestructive. Direct methods are related to measurements taken directly on the plant, are important for proper estimation and representative sampling, and have higher precision when well applied. In contrast, indirect methods are based on direct and/or diffuse light transmission measurements on the canopy, and nondestructive methods exist that allow the user to obtain a larger amount of data compared to direct manual methods [38,39]. An example of a nondestructive method is using deep learning techniques, in particular, convolutional neural networks.

In this regard, [40] indicates that traditional disease identification methods, which are based on naked eye observations, are time-consuming, costly and require significant effort to identify infected leaves [41], making it difficult to detect the disease in a timely manner over large areas. Therefore, it is crucial to develop objective and automated approaches for rapid and reliable disease detection [42,43].

Plant disease detection can be automated by robotics, image processing [44] and spectrophotometry to identify chemical compounds present in coffee leaves affected by rust [45], among others. In recent years, the emergence of imaging technologies coupled with machine learning (ML) algorithms has enabled the rapid and accurate identification of crop diseases [46]. Thus, the adoption of deep learning (DL) algorithms has proven to be far superior to conventional methods for crop disease detection [47]. These algorithms translate input data, such as images of affected plants, into valuable information for the identification of specific crop diseases [43,47]. The use of DL, therefore, involves training a network to learn the underlying features of the images, allowing the identification of subtle disease symptoms that traditional image processing methods are unable to detect [48]. In this way, it allows the model to learn so that when new digital images are introduced, the model produces automatic responses due to the prior learning process [43].

A recent study has demonstrated the potential of using DL imaging to detect plant diseases. Ref. [49] used images of robusta coffee leaves with visible mites and red spots (denoting the presence of coffee rust) for infected cases and images without such structures for healthy cases by using machine learning techniques such as artificial neural networks, genetic algorithms and clustering, demonstrating the performance of machine learning logarithms for image segmentation and classification related to plant disease recognition.

This research addresses the problem of the early identification of coffee leaf rust and provides an estimate of the severity of the disease on coffee plants in agroforestry systems in the provinces of Jaén and San Ignacio in the Cajamarca region of Peru. The study aims to propose a methodology for the timely detection of coffee leaf rust by characterizing coffee agroforestry systems, capturing information on the disease in images and then applying a segmentation approach to identify and estimate the severity of the disease.

2. Materials and Methods

2.1. Overview of the Study Area

The evaluation area corresponds to the districts of San José del Alto in the province of Jaén and that of Chirinos in the province of San Ignacio in the Cajamarca region of northern Peru (Figure 1). The district of Chirinos (78°53′54.33″ W, 5°18′17.03″ S) is located in the jungle at an altitude of 1858 masl; its climate is cold in the highlands and hot in the lowlands [50]. It covers an area of approximately 352.00 km^2 [51]. The area's economy has been centered on coffee production for decades, which is evident in the levels of local knowledge, where producers routinely extract specialty level coffee; most of the farms are organic by default [52]. San José del Alto, the district capital, is the least developed urban population center in the entire province of Jaén, located in the ecoregion of Yunga Fluvial at 1500 m above sea level. It has a population of 175 inhabitants and a land area of 634.11 km^2 [53]. Ninety percent of the families are dedicated to planting and harvesting coffee, and due to its geographic location, climate and soil, they grow different varieties of coffee such as Catimor, Caturra, Pache, Costa Rica and Tipica [54]. The research was carried out in two agroforestry systems where five coffee varieties were identified (Pache, Caturra, Bourbon, Geisha and Catimor), with forest species between 3 and 12 years old.

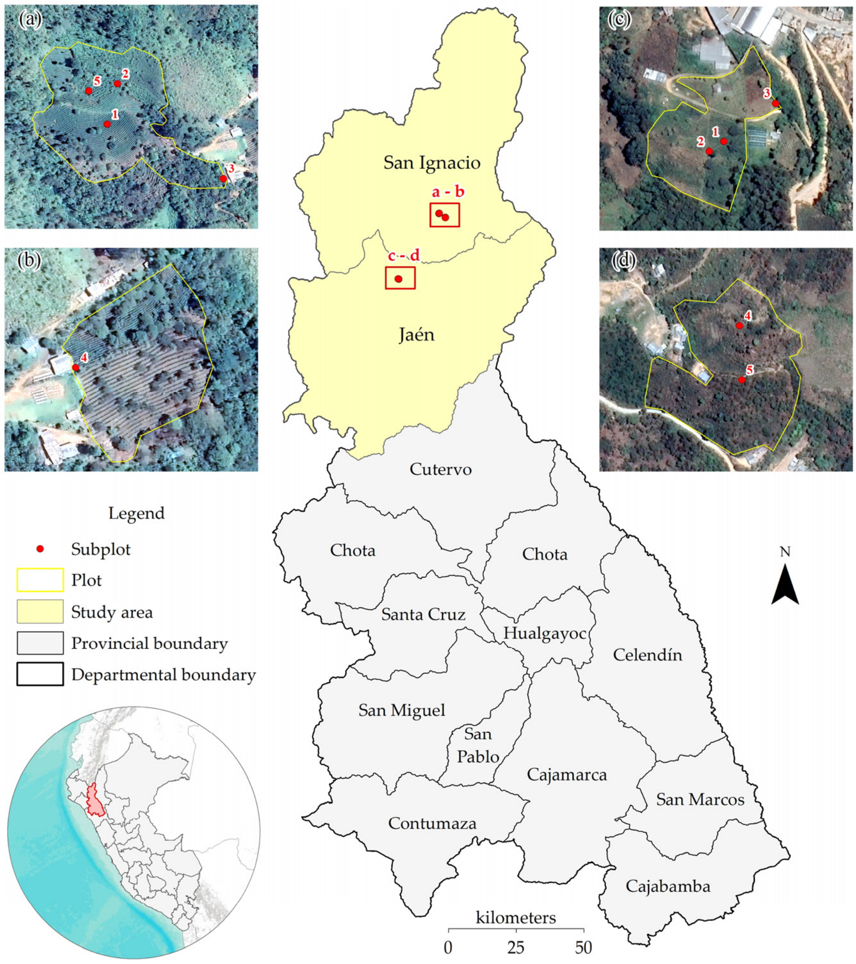

Figure 1. Location of the study area, (**a**,**b**) agroforestry system at Finca "La Palestina" and (**c**,**d**) agroforestry system at Cooperativa Agraria Cafetalera "La Prosperidad".

2.2. Field Data Collection

Four shade-grown coffee plots were selected, from which ten subplots were chosen, five in the district of San José del Alto, province of Jaén, and five in plots in the district of Chirinos (Table 1).

Table 1. Sampling points of the plots under study.

Province	District	Association or Cooperative	Plot	Subplot	Longitude	Latitude
Jaén	San José del Alto	Finca "La Palestina"	1	1	−78.8971	−5.3089
				2	−78.8972	−5.3090
				3	−78.8966	−5.3085
			2	4	−78.8764	−5.3225
				5	−78.8764	−5.3230
San Ignacio	Chirinos	Cooperativa Agraria Cafetalera "La Prosperidad"	1	1	−79.0338	−5.5280
				2	−79.0337	−5.5274
				3	−79.0321	−5.5288
			2	4	−79.0318	−5.5281
				5	−79.0341	−5.5275
Total			4	10		

Characterization of the Agroforestry Systems

In the two agroforestry systems, the number of plots, the location, the variety of coffee in each plot, the age, the number of forest plantations and the fruit species in the plots were characterized (Table 2).

Table 2. Forest species identified for each agroforestry plot.

Plot	Lot	Variety	Distance	Age	Forestry
Prosperidad	1	Pache	0.8 × 2.5	8	10
	2	Caturra	0.8 × 2.5	8	7
	3	Bourbon	0.8 × 2.5	8	8
	4	Geisha	0.8 × 2.5	12	6
	5	Catimor	0.8 × 2.5	12	8
Palestina	1	Geisha	1 × 2	4	3
	2	Catimor	1 × 2	3	3
	3	Caturra	1 × 2	12	12
	4	Pache	1 × 2	11	5
	5	Bourbon	1 × 2	15	7

A visual tour of the agroforestry systems under study was conducted, defining the typologies depending on the species associated with coffee and their function. The biophysical variables (access, slope) and vegetation variables (phytosanitary status, coffee tree strata and canopy cover) were evaluated in each farm. In addition, information on the coffee and the geographic coordinates of the center of the plot, the number and varieties of coffee plants, and the number and botanical names of the shade trees were recorded for each plot. The percentage of shade was estimated using the HabitApp application (https://play.google.com/store/apps/details?id=com.scrufster.habitapp&hl=es&pli=1), and the age of the forest species and of the crop were identified through consultation with the owners of the plots [16,55]. For the classification of the coffee agroforestry systems, the categories proposed by [56,57] and described in Table 3 were used.

Table 3. Classification of coffee agroforestry systems.

N	Category	Description	Source
(1)	Rustic	Low density of introduced coffee plants in natural vegetation, generally high plant diversity with at least three strata and canopy covers greater than 70%.	[58]
(2)	Traditional polycultures	Higher density of coffee plants and the introduction of exploitative species (e.g., fruit, medicinal, timber); canopy cover is between 40 and 70%.	[59–61]
(3)	Commercial polycultures	Intensive coffee production systems; consequently, density is high, associated tree species diversity is low, all species have some purpose for exploitation and canopy cover is in the range of 30–40%.	[59,60]
(4)	Shade monocultures	Systems where coffee is the only crop and shade is provided by two or three tree species, regular pruning is applied and canopy cover is no more than 30%.	[58,59,62]

2.3. Estimation of Rust Severity by Deep Learning

Figure 2 shows the process of estimating rust severity using deep learning. The procedure consisted of acquiring photographs of coffee leaves, then applying two convolutional neural networks (CNNs), MobileNet and VGG16, to finally estimate the severity levels using SENASA and SENASICA methodologies.

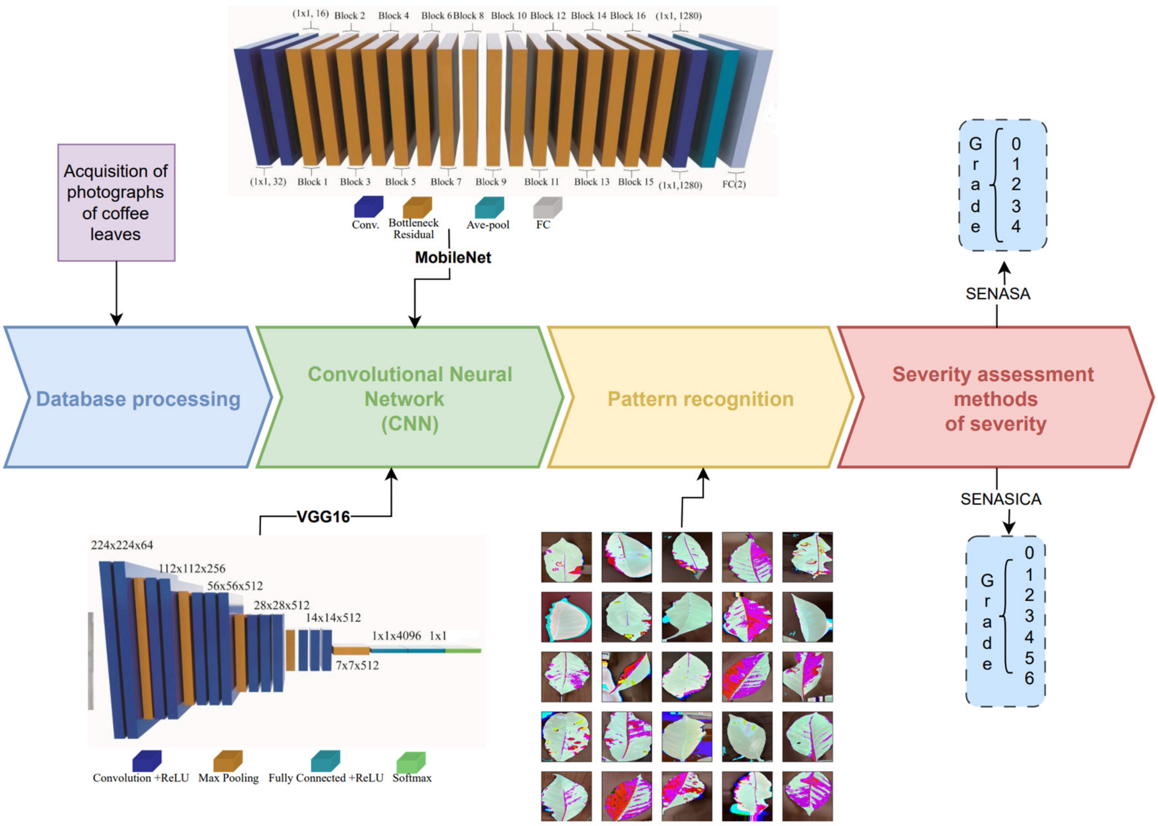

Figure 2. Methodological process to estimate rust severity using deep learning.

MobileNet and VGG16 are two pre-trained CNN architectures widely used in DL. MobileNet significantly reduces the number of parameters and computational operations compared to traditional convolutions, is much faster in terms of inference and has a much smaller model size [63]. VGG16 has demonstrated exceptional performance on image classification tasks, is relatively simple and easy to understand, has been pre-trained on large datasets, and is capable of capturing complex and detailed image features [64].

To determine the sample size and the type of sampling for the epidemiological surveillance of coffee rust, a review of the existing literature was carried out, verifying different ways of sampling. For example, ref. [65] developed their study on the epidemiology of rust on 15 coffee trees randomly chosen in 1 ha, with 4 branches marked per coffee tree. In Puerto Rico, ref. [66] demonstrated that the best system to evaluate incidence was to sample 20 coffee plants (approximately 1 coffee plant out of every 60 in the lot) in 4 parallel transects, with 5 plants sampled in each transect separated by 5 plants each, evaluating 20 leaves in the middle third of each plant.

With respect to sampling, the methodology of sentinel plots was evaluated, which is defined as fixed plots that are visited periodically to monitor the spread of a disease at the scale of a territory [67]. They allow the collection of information on the disease and generate knowledge on its biology, ecology and epidemiology. In particular, the data are useful for building prognostic models. Frequently, sampling along a route that the evaluator makes through the plot to be sampled is preferred. This path can be linear, zigzag or "W" shaped [67]. A general rule of thumb is that it is better that the sampled plants cover the plot extensively [68].

The important thing is to define a practical system that causes the least risk of error in the estimates. In this context, the present study was carried out in fixed plots with sampling in five subplots in each location, composed of one plant per point, totaling fifty plants, five for each lot under study, with three branches from each plant evaluated (one from the lower part, one from the middle part and one from the upper part) [29,49]. In addition, the total number of leaves and the number of leaves with rust in each of the levels were verified [50]. From each selected branch, four leaves were taken per stratum (low, medium and high) [69]. The evaluation was visual; the signs of the presence of rust in the coffee plants were identified by the pale-yellow spots on some plants, while brown spots were found on others and, in some cases, plants were found without leaves [15,56,57]. The affected leaves were photographed in order to determine the total area of the leaf and the area affected by the rust stain on the coffee plant; this allows the percentage of the area affected by the disease (severity) to be calculated [70]. The leaves were photographed individually with a white background [71] using a Nikon COOLPIX model P1000 digital camera. Each image was labeled for subsequent identification and processing [72].

The scale proposed by the National Agricultural Health Service (SENASA) of Peru was used to classify the severity of coffee rust, and the scale proposed by the National Service of Health, Safety and Agrifood Quality (SENASICA) of Mexico was used as an alternative method of visual evaluation (Figure 3). In both cases, the mobile application Leaf Doctor (https://www.quantitative-plant.org/software/leaf-doctor) was used to estimate the area of diseased tissue [73]. The application has an extremely user-friendly interface and only requires the user to take a picture with the device in the app itself. The resulting image indicates the color of healthy and infected leaf tissues, and after a few seconds of processing, the app shows the percentage of leaf area affected by the pathogen [73,74].

SENASA has established a scale of severity related to the percentage of rust present on coffee leaves, with a quantification range from 0 to 4: grade 0 indicates healthy leaves or no visible symptoms; grade 1 means that the symptoms are visible, covering from 1 to 5% of the total area of the leaf; in grade 2, the spots begin to unite and occupy from 6 to 20% of the healthy area; in grade 3, the leaves begin to necrotize in a very noticeable way, affecting 21 to 50% of the healthy area; and finally in grade 4, more than 50% of the leaf area is affected with rust. SENASICA, on the other hand, quantifies the severity of *H. vastatrix* through six levels of disease. The diagrammatic scale is shown in Figure 3: grade 0 is for healthy leaves or leaves without visible symptoms; grade 1 is for leaves with visible symptoms and the first chlorotic spots; in grade 2, the spots begin to unite and occupy 2% of the healthy area of the leaf; in grades 3, 4 and 5, the spots unite and occupy 7%, 20% and 45% of the healthy area of the leaf, respectively; and in grade 6, more than 70% of the leaf area is affected.

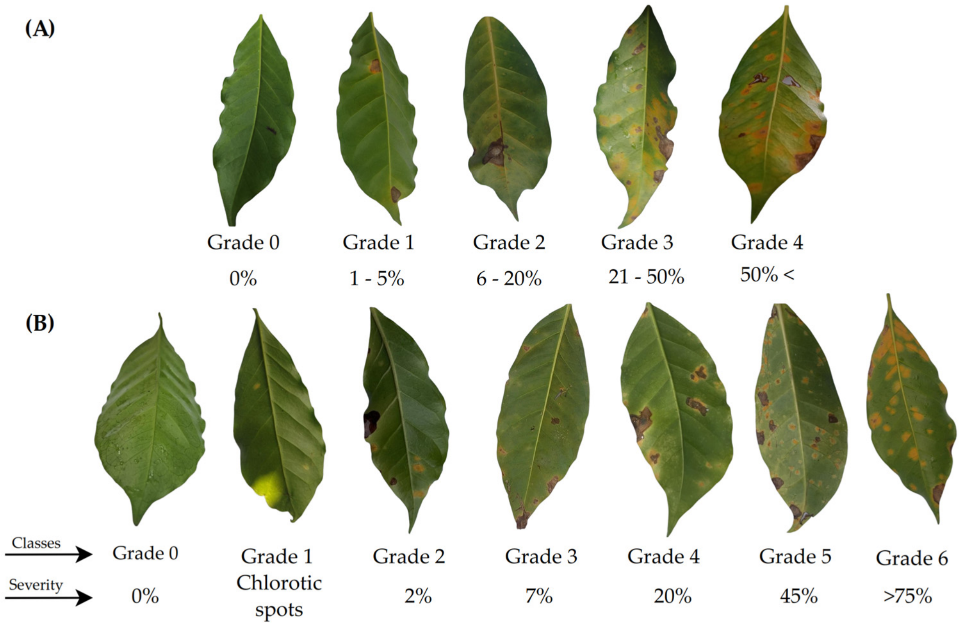

Figure 3. Coffee rust severity scale according to the methodologies of (**A**) SENASA of Peru and (**B**) SENASICA of Mexico.

To determine the severity level, the infection index and the degree of rust severity (%) were calculated [74]; the equations are detailed in Table 4.

Table 4. Equations used for each proposed scale.

Proposed Scale	Infection	Severity
SENASA	$Infection\ rate = \frac{N°\ spots \times (N°\ diseased\ leaves)}{(Total\ number\ of\ leaves)}$	$\%\ severity = \frac{(Necrotic\ area)}{(Total\ leaf\ area - Necrotic\ area)}$
SENASICA	$N°\ lesions\ per\ cm^2 = \frac{N°\ number\ of\ leaves \times 100}{(Leaf\ area)}$	$Damaged\ leaf\ area\ \% = \frac{Leaf\ blight\ area}{Leaf\ area} \times 100$

2.4. Image Processing

Once a large collection of coffee tree image data was gathered, the next step was to meticulously clean and pre-process the collected images [75,76], and a cropping tool was used to remove unwanted areas from the images [77]. From this collection, a sample of 319 images with different levels of damage were selected, resized and normalized to improve quality and uniformity and ensure the compatibility of the image processing algorithms [76]. Illumination conditions were prioritized in each image, as this reduces the computational load on the model, accelerates the convergence and classification of the leaves, and allows predictions higher than 90%.

The images were resized (224 × 224 pixels) because convolutional neural networks (CNNs), which require the input images to be the same size, reduce the computational load and speed up model training without sacrificing the quality of the information. The images were normalized (pixel values were divided by 255), ensuring that the pixel values were in a consistent range, helping the model to learn efficiently. DL models perform better when the input data is normalized—this speeds up the training process by allowing the model to converge faster. Finally, the data were augmented (20%) from the existing data by transformations such as rotations, translations and scaling, allowing a larger and more varied dataset to be created, which reduces the risk of overfitting and significantly improves the performance of the deep learning models.

2.5. Convolutional Neural Networks and Deep Learning Architectures

The system involved three phases: image preprocessing, feature extraction and classification (Figure 4) [72]. The following aspects were considered:

1. Annotation of the dataset: The data were labeled according to the qualitative ordinal scale.
2. Dataset division: To validate and evaluate the deep learning model, the dataset was divided into training, validation and test sets, with 70% for training, 20% for validation and 10% for testing [72]. The models were trained over a span of 50 epochs.
3. Data preprocessing: Two preprocessing operations were performed before inputting the images into the CNN.

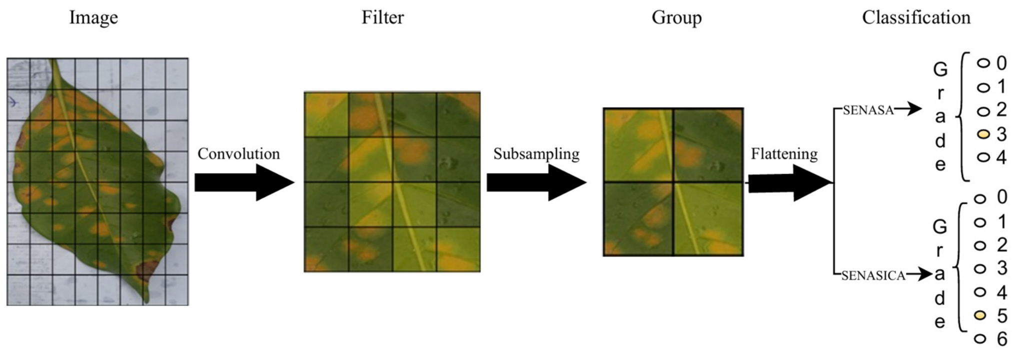

Figure 4. Convolutional neural network structure for classifying severity grades.

As for the deep learning architectures, two CNN architectures (MobileNet and VGG16) were used for the training and validation of the models. CNNs process unstructured image inputs and accurately map them to the appropriate output classes [78]. VGG-16 is a CNN comprising 16 weight layers, including 13 convolutional layers and 3 fully connected layers. This model evaluates networks and increases depth using a minimal ($3 \times 33 \times 3$) convolutional filter architecture [40,77]. For its part, MobileNet includes three convolutional layers. The growth layer is the primary layer with dimensions of 1×1. It is a computationally efficient and accurate model, suitable for mobile applications, with smaller datasets, making it ideal for real-world scenarios [40,78,79]. For the implementation of the proposed models on the dataset, Google Colab pro, Python version 3.8, PyTorch tool, NVIDIA GTX 1070 GPU and OpenCV 3.4.2 were used [40].

2.6. Metric Evaluations

The performance of the leaf and lesion segmentation models was evaluated individually using the following four metrics: *accuracy*, *precision*, *recall* and *F1 Score* [71]. *Accuracy* is the proportion of the total number of predictions that correctly estimated disease severity (Equation (1)). *Precision* is the ratio of correctly classified cases to the total number of misclassified cases and correctly classified cases (Equation (2)). *Recall* is the ratio of correctly classified cases to the total number of misclassified cases and correctly classified cases

(Equation (3)). Finally, *F1-Score* is a metric that combines precision and recall and provides a summary of the predictive power of a model (Equation (4)) [40].

$$Accuracy = \frac{PV + NV}{PV + NF + NV + PF} \quad (1)$$

$$Precision = \frac{PV}{PV + PF} \quad (2)$$

$$Recall = \frac{PV}{PV + NF} \quad (3)$$

$$F1\ Score = \frac{2\ X\ precision\ x\ recall}{precision + recall} \quad (4)$$

where *PV* are the true positives, *PF* the false positives, *NV* the true negatives and *NF* the false negatives.

3. Results

3.1. Characterization of Agroforestry Systems

Chirinos district plot: Inga edulis and Persea americana are the abundant species in lot 1; other species that were also found but with less presence were Albizia, Pinus and Colubrina glandulosa. Likewise, in lot 2, Persea americana was the most fertile species; species found in lesser quantities included Quercus robur, Colubrina glandulosa Perkins, Musa paradisiaca, Eucalyptus, Pinus and Inga edulis. In lot 3, similar quantities of the following species were found: Persea americana, Musa paradisiaca, Quercus robur, Juglans regia, Pinus, Eucalyptus, Vochysia vismiifolia and Inga edulis. In the fourth lot, as in lot 3, the quantities of species were similar, and in lot 5, Inga edulis was the species found in the highest quantity, and other species were found in lesser quantities, such as Quercus robur, Persea americana, Musa paradisiaca, Calycophyllum candidissimun, Pinus and Eucalyptus.

Plot of the District of San José del Alto: In lot 1, there were species found in similar quantities, such as Pinus, Inga edulis, Solanum melongena, psidium, Musa paradisiaca, Persea americana and Pouteria lúcuma. In lot 2, Persea americana was the most abundant species, but there were also species found in smaller quantities, such as Quercus robur, Colubrina glandulosa Perkins, Eucalyptus, Pinus and Inga edulis. In lots 3, 4 and 5, as in lot 1, there was a diversity of species common to the area, but the quantities were identical (Table 5).

As presented in Figure 5, in the Chirinos plot, using HabitApp, the means of the percentages of shade of lots 1–5 are as follows: lot one 53.9, lot two 29.5, lot three 43, lot four 64.9 and lot five 47.15; the means using the visual template are lot one 55.5, lot two 25.5, lot three 45.5 and lot four 67. The standard deviation in HabitApp for lot one is 11.33, lot two is 7.86, lot three is 8.94, lot four is 15.48 and lot five is 11.78; the standard deviation in the visual template for lot one is 13.56, lot two is 14.31, lot three is 16.69, lot four is 17.43 and lot five is 14.54. The minimum and maximum values that stand out the most in HabitApp are those for lot one, and the values that stand out the least are those for lot two; by contrast, in the visual template, the lot that is the most relevant is lot four, and the lot that stands out the least is lot two, which is the same as when using the application. In batch 3 and 4 in HabitApp, there are two outliers in each batch mentioned. In San José del Alto, the averages of the shade percentages of lots 1–5 are lot one 32.6, lot two 50.35, lot three 42.25, lot four 62.6 and lot five 41.7; on the other hand, using the visual template, the averages are lot one 37.5, lot two 47, lot three 36.5, lot four 59. 5 and lot five 45.5. The standard deviation data obtained are lot one 16.12, lot two 14.86, lot three, 20.10, lot four 8.65 and lot five 18.84, and for the visual template, they are lot one 17.73, lot two 15.07, lot three 21.34, lot four 12.34 and lot five 13.56. In the minimum and maximum values in the application, the values that stand out the most are for lot three; in the visual template, lot three also stands out. In lot four, using HabitApp, there are two outliers; in lot four of the visual template, there are also two outliers, and in lot three there is one outlier.

Table 5. Forest species by lot and study locality.

Species	Lot 1		Lot 2		Lot 3		Lot 4		Lot 5	
	Ch	SJA	Ch	SJA	Ch	SJA	Ch	SJA	Ch	SJA
L. edulis	+	+	+	+	+		+	+	+	+
P. americana	+	+	+		+	+		+	+	
Albizia	+									
Pinus	+	+	+	+	+	+	+	+	+	
C. glandulosa	+									
S. melongena		+				+				+
Psidium		+		+		+				
M. paradisiaca		+	+	+	+		+	+	+	+
P. lúcuma		+								
Q. robur			+	+	+	+	+	+	+	+
C. glandulosa Perkins			+							
Eucalyptus			+		+	+		+	+	+
C. sinensis				+			+	+		
J. regia					+					
V. vismiifolia					+					
O. pyramidale						+	+			+
Cedrus						+				
F. luschnathiana						+				+
C. lechleri						+				
A cherimola						+				
P. Caerulea						+				
M. indica							+			

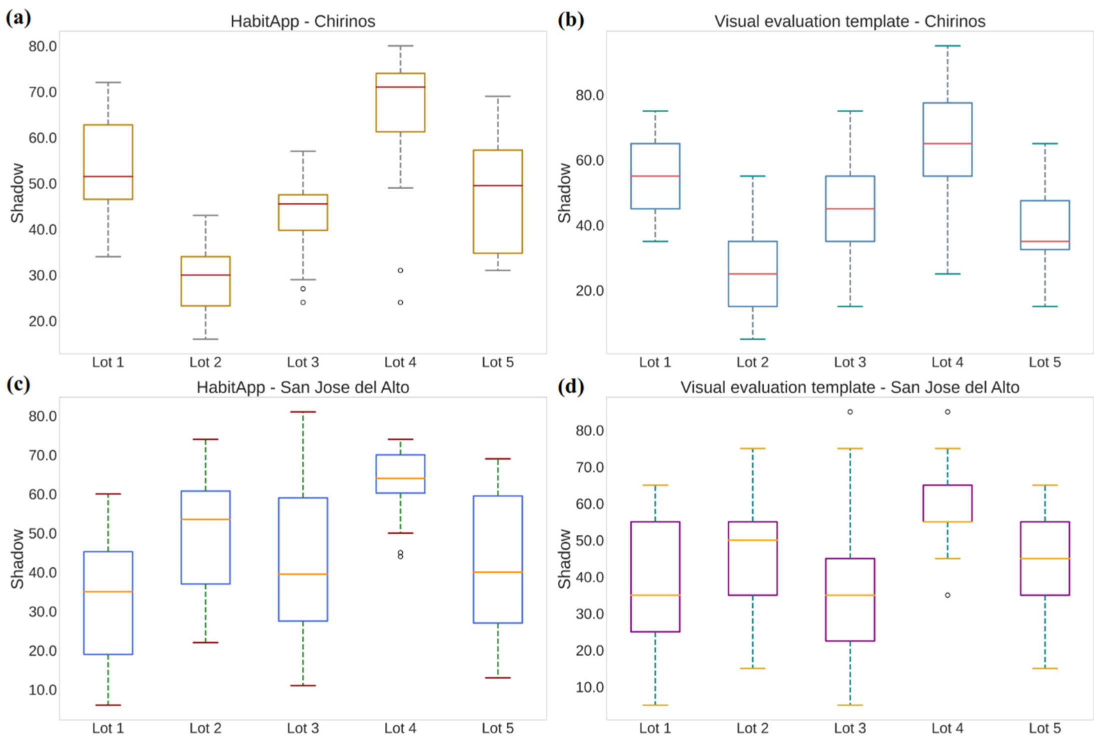

Figure 5. Percentage of shade in batches: (**a**) using HabitApp, (**b**) using a visual template in Chirinos, (**c**) using HabitApp, (**d**) using a visual template in San Jose del Alto.

With respect to the classification of the coffee agroforestry system in each lot and considering only the type of agroforestry system, traditional polycultures were the most used systems, while rustic systems and shade monocultures were the least implemented. In addition, of all the lots evaluated, no commercial polycultures were identified because although it is true that there was a high density of coffee, the majority of tree species (<3) did not have exploitation purposes (Figure 6).

Figure 6. Characterization of agroforestry systems with coffee: (**a**) shade monoculture, (**b**) traditional polyculture, (**c**) rustic system, (**d**) traditional polyculture, (**e**) traditional polyculture, (**f**) traditional polyculture, (**g**) shade monoculture, (**h**) rustic system, (**i**) traditional polyculture, (**j**) shade monoculture.

3.2. Behavior of Deep Learning Models

Using the evaluation set for SENASA and SENASICA classification, CNNs were used. Figure 7 presents the performance of the MobileNet and VGG16 models on the SENASA and SENASICA datasets, respectively. In matrices (a) and (b), corresponding to SENASA, high performance is observed in the "GRADE 0" and "GRADE 1" classes, with 96 and 109 instances correctly classified in (a) with MobileNet and 95 and 108 in (b) with VGG16. The other classes, however, show medium performance in "GRADE 2", "GRADE 3" and "GRADE 4", with 71, 23 and 3 instances correctly classified in (a) with MobileNet and 70, 22 and 4 in (b) with VGG16. In matrices (c) and (d), corresponding to SENASICA, there is a high performance in "GRADE 0" and "GRADE 1", with 96 and 78 instances correctly classified in (c) with MobileNet and 92 and 78 in (d) with VGG16. The "GRADE 2", "GRADE 3", "GRADE 4", "GRADE 5" and "GRADE 6" classes show medium performance with 17, 43, 59, 24 and 4 instances correctly classified in (c) with MobileNet and 16, 40, 58, 25 and 3 in (d) with VGG16.

Table 6 shows the performance metrics of the MobileNet and VGG16 models of the SENASA classification in different grades, presenting significant variations in terms of precision, recall, F1-score and accuracy. For the MobileNet model, the "GRADE 0" and "GRADE 1" classes show high precision (0.9697 and 0.9646, respectively) and recall (0.9696 and 0.9732), indicating high performance in these classes. However, the metrics for "GRADE 2", "GRADE 3" and "GRADE 4" are average, with an accuracy of 0.9595, 0.8519 and 0.75, respectively, and an F1-score of 0.9726, 0.8846 and 0.5455, respectively, to correctly classify the classes. In the case of the VGG16 model, a similar pattern is observed, with high precision and recall values for "GRADE 0" of 0.9793 and 0.9596, respectively, and "GRADE 1" of 0.9557 and 0.9643, respectively, while "GRADE 2", "GRADE 3" and "GRADE 4" present average metrics, especially for "GRADE 4", where the F1-score is

0.6667. In general, both models show good performance in the dominant classes, correctly classifying the different classes.

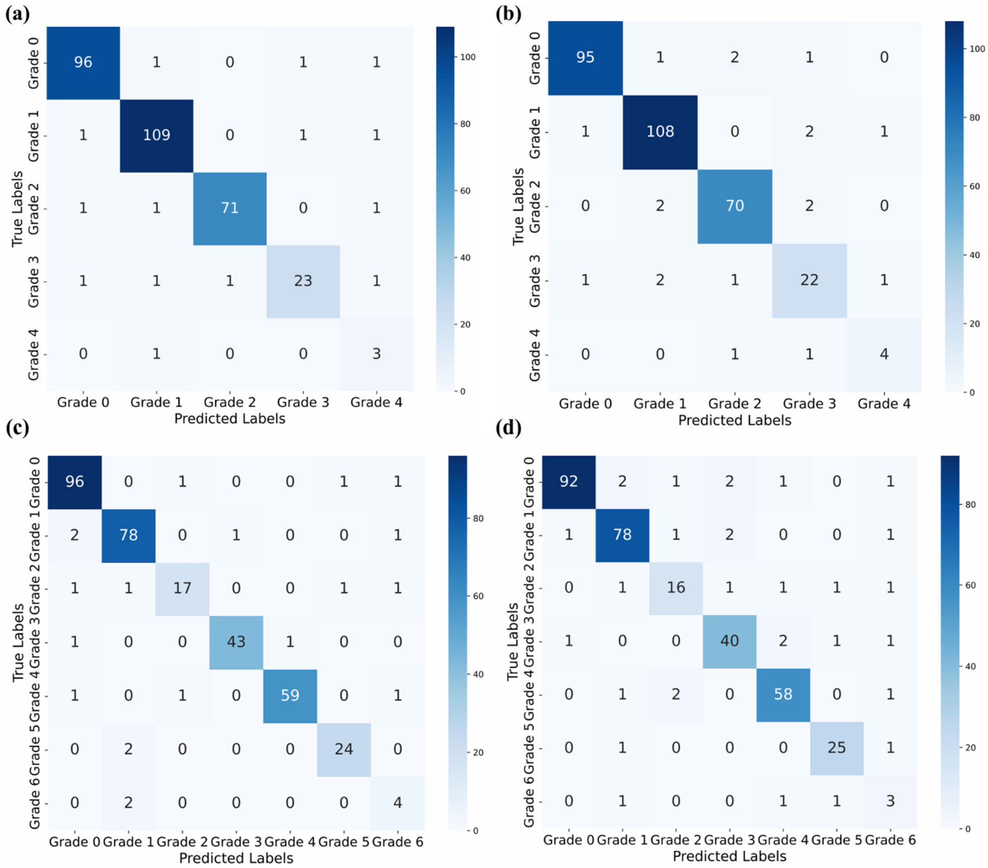

Figure 7. Confusion matrix: (**a**,**b**) SENASA and (**c**,**d**) SENASICA using MobileNet and VGG16.

Figure 8 shows the accuracy of MobileNet (blue solid line) and VGG16 (orange dashed line) models for SENASA classification over 50 training epochs. Initially, VGG16 shows a rapid increase in accuracy, outperforming MobileNet. However, from epoch 30 onward, MobileNet shows a sustained improvement, reaching and surpassing VGG16's accuracy toward the end of training from 91 to 94%. This indicates that although VGG16 has better initial performance, MobileNet demonstrates better long-term efficiency.

Table 6. Evaluation metrics for SENASA classification.

Network	Grade	Precision	Recall	F1-Score	Accuracy
MobileNet	0	0.9697	0.9696	0.9697	0.9696
	1	0.9646	0.9732	0.9689	0.9732
	2	0.9861	0.9595	0.9726	0.9595
	3	0.9200	0.8519	0.8846	0.8519
	4	0.4286	0.7500	0.5455	0.7500
VGG16	0	0.9793	0.9596	0.9694	0.9596
	1	0.9557	0.9643	0.9600	0.9643
	2	0.9459	0.9459	0.9459	0.9459
	3	0.7857	0.8148	0.8000	0.8148
	4	0.6667	0.6667	0.6667	0.6667

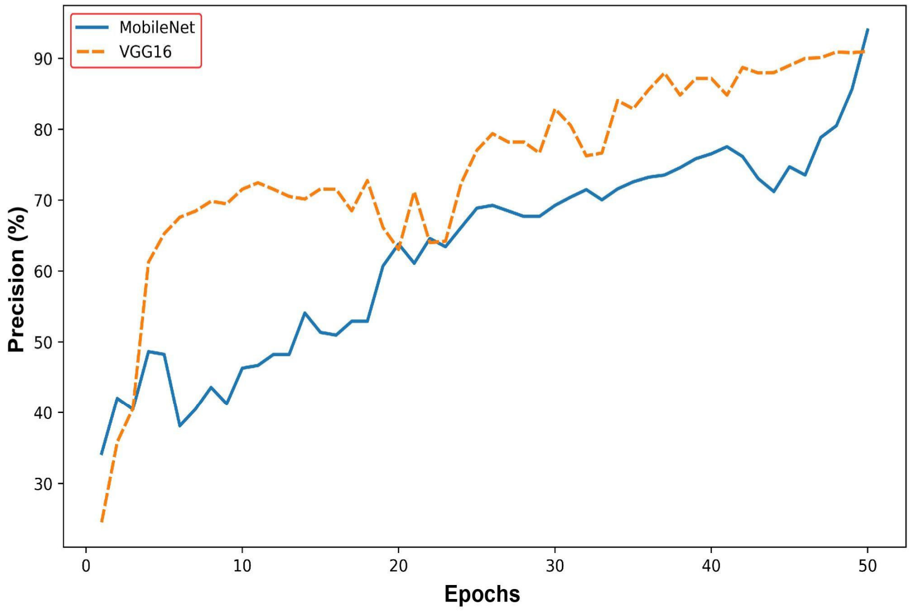

Figure 8. Model accuracy for SENASA.

Table 7 shows the performance of the MobileNet and VGG16 models of the SENASICA classification in several evaluation metrics across seven classes (grade 0 to 6). For MobileNet, it is observed that accuracy, recall and F1-Score are high for most classes, especially for grades 0, 1, 3 and 4, with accuracy values above 0.9. However, average performance is evident for grade 6, with an F1-Score of 0.5714, indicating a lower ability to handle this specific class. In comparison with VGG16, it shows performance with high accuracy values for grades 0, 1, 3 and 4, with the metrics being lower overall when compared to MobileNet. Particularly for grades 2 and 6, VGG16 presents F1-Scores of 0.7805 and 0.4000, respectively, highlighting a lower effectiveness in these classes. The MobileNet model shows better performance, especially in accuracy and F1-Score metrics, while VGG16 exhibits higher variability and significantly lower performance across classes.

Table 7. Evaluation metrics for SENASICA classification.

Network	Grade	Precision	Recall	F1-Score	Accuracy
MobileNet	0	0.9505	0.9696	0.9600	0.9696
	1	0.9397	0.9512	0.9454	0.9512
	2	0.8947	0.8095	0.8500	0.8095
	3	0.9772	0.9556	0.9662	0.9556
	4	0.9833	0.9516	0.9672	0.9516
	5	0.9230	0.9230	0.9230	0.9230
	6	0.5000	0.6666	0.5714	0.6666
VGG16	0	0.9787	0.9293	0.9533	0.9293
	1	0.9286	0.9397	0.9341	0.9397
	2	0.8000	0.7619	0.7805	0.7619
	3	0.8889	0.8888	0.8889	0.8888
	4	0.9206	0.9354	0.9280	0.9354
	5	0.8928	0.9259	0.9091	0.9259
	6	0.3333	0.5000	0.4000	0.5000

Figure 9 shows the accuracy of the MobileNet (blue solid line) and VGG16 (orange dashed line) models over 50 training epochs. Initially, VGG16 outperforms MobileNet, showing a rapid increase in accuracy. However, from epoch 25 onward, MobileNet starts to improve more consistently, reaching 92% accuracy, which is higher than VGG16's 90%

accuracy, in the last few epochs of training. This behavior suggests that, although VGG16 achieves high performance quickly, MobileNet demonstrates greater efficiency and sustained improvement over the long term.

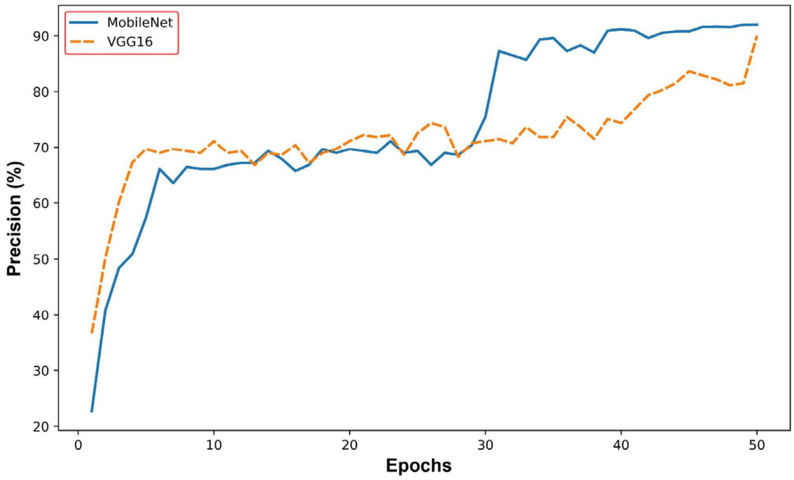

Figure 9. Model accuracy for SENASICA.

According to the SENASA classification, the overall accuracy of the model was 94% for MobileNet and 91% for VGG16 after the 50 epochs (see Figure 8). However, for SENASICA, the accuracy was 92% for MobileNet and 90% for VGG16 (see Figure 9).

4. Discussion

Agroforestry systems are important for biodiversity conservation and provide ecosystem services such as increased soil fertility, microclimate regulation through shade and disease mitigation through various trophic and abiotic interactions [80,81]. Coffee is planted together with forest, including woody, leguminous and secondary forest species, where the incorporation of nutrients is important as a result of the decomposition of vegetative residues [82,83]. Species associated with agroforestry coffee in the study area were represented by Inga edulis, Persea americana, Musa paradisiaca, Quercus robur, Juglans regia, Pinus, Eucalyptus, Solanum melongena, Psidium, Pouteria lúcuma and Vochysia vismiifolia. It has been reported that woody plants can reduce the growth of characteristic coffee plantations [84]. However, other species can contribute to the carbon stock and generate extra income for farmers [82,85].

The shading percentages of forest plantations in PBS ranged from 25.5 to 67.5%. It has been reported that the best yields are obtained when coffee is shaded from 23 to 38% [82]. On the other hand, studies have shown that the use of shade improves the production and quality of beans, favors the presence of some pollinators, presents greater species diversity [82,86,87] and supports organic coffee production with artisanal or semi-automated processing [88]. However, other studies report that high levels of shade favor the reproduction and dispersion of pests and diseases [89,90], with greater incidence in the older stages of plantations [90] and a reduction in photosynthetically active radiation that affects the growth of branches [91,92].

Coffee leaf rust caused by *Hemileia vastatrix* Berk. is one of the worldwide diseases and threatens coffee production in many countries [93]. This disease causes a decrease in the yield and quality of coffee beans [94,95]. Applying practical and reliable methods to quantify severity and propose strategies for disease management is very important. Disease quantification can be achieved by assessing incidence (percentage of leaves with disease symptoms) and severity (percentage of leaf tissue area injured) [71]. This study compares two methods to determine the severity of coffee plantations proposed by SENASA and SENASICA using the Leaf Doctor app. The results reported that at the SENASA methodology level, severity ranged from grade 1 to 2, while at the SENASICA methodology level, higher percentages were reported in grades 1, 4 and 3. The results are similar to those reported in [94], who found a range of 0 to 52.15% of the leaf area affected [94], or the results reported in India, where the average severity of infection ranged from 1.34 to 32.67% [96]. Ref. [24] reported that rust incidence can increase during harvest from 4 to 36% [15,24], considering that severity levels can increase in the dry season compared to the wet season [15]. On the other hand, the high levels of severity in the study area could be related to the increase in temperature and relative humidity, which generate suitable conditions for the development of the disease [97]. This could be due to a latency period of the pathogen when the temperature is high or the negative effect of the maximum temperature on host physiology and resistance. In fact, climate change (e.g., drought, extreme temperatures, intense rainfall) could have a negative impact on production and lead to decreases in yield and the loss of optimal areas for coffee since coffee is a crop very sensitive to variations in temperature and rainfall [98,99], exerting a negative impact in the Andes and the Amazon [100].

The results obtained from the evaluation of the MobileNet and VGG16 models using the SENASA and SENASICA datasets reveal interesting patterns in terms of performance and efficiency in applying DL. In general, both models show high performance in the "Grade 0" and "Grade 1" classes, with the correct classification of most instances in these grades, suggesting a robust ability to identify dominant classes. However, both MobileNet and VGG16 present average performance in the less frequent classes, such as "Grade 2", "Grade 3" and "Grade 4", indicating lower effectiveness in classifying these categories. This could be due to the smaller number of instances available for these classes, which limits the model's ability to learn distinctive patterns. It is remarkable how the models show differences in their behavior during training. The SENASA classification indicates that VGG16 initially outperforms MobileNet, but MobileNet manages to outperform VGG16 toward the end of training, reaching 94% accuracy. This behavior suggests that MobileNet, although initially slower in learning, demonstrates a greater capacity for sustained improvement over time. A similar pattern is observed in the SENASICA classification, where MobileNet again shows a more consistent and sustained improvement, reaching a superior accuracy of 92% at the end of training compared to 90% for VGG16. At the level of accuracy of the results, they show consistency with those reported by other studies, such as [101], which achieved an accuracy of 91% for the estimation of disease severity (healthy, general and severe), ref. [102], which obtained an accuracy of 86.51% for the estimation of severity in five classes, or those reported by [103], presenting accuracy values around 98% and 96% for the classification of coffee diseases in Brazil.

One of the limitations of the proposal is that the study has not analyzed the relationship of meteorological variables with the incidence or severity of coffee rust. Since these variables should be constructed from daily station records, at the daily level, in addition to the averages and sums of meteorological variables, prolonged leaf humidity values (at least 6 h) should be considered because the germination of *H. vastatrix* uredospores occurs if the leaf is wet. High relative humidity (above 95 percent) would also have to be considered as an indirect measure of continuous leaf wetness [104]. In addition, periods of leaf wetness should be analyzed at night (from 20 h to 8 h) since infection occurs preferentially with little or no light [105]. Also, days of precipitation greater than or equal to 1 mm should be considered rainy according to the criteria used by [106].

In this work, we propose the application of DL, integrating convolutional neural networks to automate the detection of coffee rust from field images collected through smartphones. The results obtained are promising for this area of study. This highlights the importance of the early detection of coffee rust to reduce its impact on crop production and yield. However, it is necessary in future studies to integrate convolutional neural networks to classify different coffee leaf diseases such as fumagina, Cercospora (cercosporiosis), Phoma and leaf miner. Likewise, the implementation of studies related to the effect of climate change on the areas suitable for cultivation and the impact of shade on the proliferation of pathogens in coffee crops is essential.

5. Conclusions

The agroforestry systems studied in the Chirinos and San José del Alto plots demonstrate a high diversity of forest species, with a notable prevalence of Inga edulis and Persea americana in Chirinos and a more uniform distribution of species in San José del Alto. Most of the plots use traditional polyculture systems, indicating a preference for the integration of several tree species together with coffee cultivation. The variation in the percentage of shade between plots has a direct impact on the microclimatic conditions, influencing coffee yield and the biodiversity of the agroforestry system.

Regarding the application of deep learning models to evaluate rust severity, MobileNet and VGG16 demonstrated high performance for the main categories according to the SENASA and SENASICA standards. Although both models achieved high levels of accuracy, especially for Grade 0 and Grade 1 classes, they faced challenges in the classification of less represented categories. Despite this, the results indicate a great potential for the application of these models in the evaluation of rust severity in the coffee industry, with accuracy reaching up to 97% for the most frequent classes. The implementation of these models would allow the early detection of rust, facilitating the adoption of control and mitigation measures, which would guarantee a sustainable and high-quality production.

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