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Automated Recognition Systems: Theoretical and Practical Implementation of Active Learning for Extracting Knowledge in Image-based Transfer Learning of Living Organisms

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Abstract

In our research, we propose a model that leverages transfer learning and active learning techniques to accumulate knowledge and effectively solve complex problems in the field of artificial intelligence. This model operates within a parallel learning paradigm, aiming to mimic the continuous learning and improvement observed in human beings. To facilitate knowledge accumulation, we introduce a convolutional deep classification auto encoder that extracts spatially localized features from images. This enhances the model's ability to extract relevant information. Additionally, we propose a learning classification system based on a code fragment, enabling effective representation and transfer of knowledge across different domains. Our research culminates in a theoretical and practical prototype for active learning-based knowledge extraction in various living organisms, including humans, plants, and animals. This knowledge extraction is achieved through image-based learning transfer, focusing on advancing activity recognition in image processing. Experimental results confirm that our method outperforms both baseline approaches and state-of-the-art convolutional neural network methods, underscoring its effectiveness and potential.

Keywords: Artificial intelligence (AI), Machine Learning (ML), Learning by transfer; Human Activity Recognition (HAR), Multi-Layer Perceptron (MLP).

1 Introduction

Society increasingly places significant emphasis on the generation, acquisition, and processing of data on a large scale. This is done to facilitate socio-economic processes, enhance organizational efficiency, provide access to necessary resources, and simplify human activities as a whole. The digital recording of human activities [71] and the interconnectedness of everything around us to various data sources [73] have created the need for data management tools and techniques capable of efficiently and intelligently extracting relevant information and knowledge. This, in turn, promotes standardization and progress in the understanding of living organisms (humans, animals, and plants). In recent years, efforts have been focused on standardizing knowledge related to human activities [28] as well as the life cycles of animals and plants. This has led to the expansion of data identification/retrieval and representation learning theories within the realm of artificial intelligence. Initially, the field of artificial intelligence aimed to develop "thinking machines" with general intelligence similar to humans [57]. However, this goal was deemed too ambitious and challenging to achieve directly, leading to a shift in focus towards developing AI systems capable of managing specific tasks in narrow but diverse fields [59], such as agriculture[13], healthcare [84], education [65], retail [22], and the service industry [62]. The ultimate aim is to create high-performance systems capable of processing vast amounts of information, surpassing the processing capacity of the human brain [54]. These systems will be able to perform multiple complex tasks, akin to human problem-solving, but without the potential for human errors [37]; [58]. The scientific framework of this work aligns with the process of artificial intelligence, specifically the extraction of patterns based on learned models applied to training data, which falls within the domain of transfer learning [37], [58]. The goal is to provide a prototype for generating visual knowledge about living organisms (humans, plants, and animals) through active learning and image-based transfer learning, thereby proposing a method for visual diagnostics. This approach represents a competitive classifier of data and information, minimizing annotation costs [4], utilizing EfficientNet, InceptionV3, and ResNet50 deep learning architectures with transfer learning methods for successful plant classification. Therefore, this paper addresses the following research questions:

- *To what extent can plant classification benefit from knowledge transfer in deep learning, facilitating the development of automatic plant identification systems (using vine leaves as a case study)?*
- *Which scenarios of learning through knowledge transfer facilitate improved performance in plant classification patterns using deep learning-based automatic identification systems, generating knowledge about plants through the study of vine leaves?*

The structure of the paper is as follows: Section 2 presents a literature review on various approaches related to machine learning, knowledge extraction through active learning, and knowledge transfer in living organisms (humans, plants, and animals), with a specific focus on vine leaves. This leads us to delve into deep learning through CNNs. The subsequent section provides a review of the existing knowledge in the field. Section 3 describes the adopted approach, which is then explained in the experimental results presented in Section 4. Section 5 discusses the findings and potential validity threats, while Section 6 presents the research findings, theoretical and managerial contributions, limitations, and future perspectives.

2 Literature review

Artificial intelligence (AI) has played a vital role in advancing various fields of research related to the identification and understanding of human, animal, and plant activities. This has expanded our ability to perceive and manipulate the surrounding environment [16],[46]. Machine learning, a prominent component of AI, is extensively utilized across diverse domains, ranging from object detection [84] and speech recognition [20] to protein structure prediction [74] and technical design optimization [17]. Its success stems from its capacity to learn from vast amounts of data. However, it still falls short of attaining human-level intelligence. Although there have been a few instances where AI outperforms humans in sensory tasks such as image recognition, object detection, and language translation [10], these victories contribute to the development of systems that recognize the activities of living organisms [4], [43], [11]. Systems designed to recognize the behavior of living organisms integrate human knowledge into machine learning. This integration serves several purposes: reducing the required data, enhancing the reliability and robustness of machine learning, and creating explainable machine learning systems that can understand the activities of living organisms [18]. From the perspective of knowledge in machine learning, researchers [10] distinguish between two types: "general knowledge" and "domain knowledge".

2.1 A. General knowledge

The application of artificial intelligence (AI), big data, and machine learning (ML) has significantly advanced due to general knowledge, leading to notable progress in automated recognition systems. These systems have become not only feasible but also increasingly utilized in various activities. Activity recognition systems rely on machine learning algorithms, including static and symbolic deep neural networks (DN) [10]. Deep learning techniques have been applied to diverse datasets, and the findings have been documented in specialized papers, categorized into three main currents or stages of knowledge. The first current, based on studies like [16] and [15], focuses on transfer learning techniques, such as feature and instance representation, and unsupervised learning [22], [50]. Additionally, it explores the benefits of combining mobile devices with environmental sensors to enhance knowledge in transfer learning [47], [28]. In this current, transfer learning assumes the presence of a data source and a target domain, with an established relationship between them, facilitating the transfer of knowledge [9]. This enables the generation of predictions in a target area [4] by leveraging existing knowledge [63]. Different scenarios of knowledge transfer have been identified, including inductive learning (where the target task differs from the source task), transductive learning (where the target and source tasks are the same but the domains differ), and unsupervised learning (where the target task is different but related to the source task). These types of knowledge transfer serve as stages of discovery for active learning about living organisms [47], [28]. The second current emphasizes the idea that knowledge transfer aids in the discovery of new data through active learning. It encompasses homogeneous learning (transfer of knowledge within similar spaces/contexts), heterogeneous learning (transfer of knowledge between different characteristic spaces/contexts), and negative learning (where negative transfer techniques help select the most useful information) [79]. Active learning generates activity recognition models from small datasets, requiring decisions to query and update the model as new data arrives in real time [66], [28]. In this way, active learning integrates with deep learning methods based on artificial neural networks [71], even in biological systems like plants [39]. The third current centers on the development of deep neural network technology [24], [36], [44], which involves multi-layered and multi-neuron models. This progress has been made possible by the availability of vast amounts of data, efficient storage and management capabilities, and advancements in processors, such as multicore and GPU graphics processors [14]. Convolutional neural networks (CNNs) have gained popularity within this current due to their ability to automatically learn and extract features from input data. CNNs consist of convolution layers for feature learning, max-pooling layers for dimensionality reduction, and fully connected layers for classification [65]. This research is frequently applied to image recognition and classification tasks [13], as CNNs can learn features, achieve human-level recognition, and adapt to new tasks through re-learning and transfer learning, thereby generating domain knowledge. Our paper aligns with the latest current, where a class of machine learning algorithms utilizes multiple layers to extract significant features gradually from input data [2]. In our experiment, we employed a multilayer perceptron architecture with several hidden layers, referring to it as a deep neural network (CNN) [77]. In this model, artificial neurons receive input values, which are individually weighted and summed using weights (wi). This process generates an activation value similar to the action potential in biological neurons [51], and the result is passed through an activation function (see Appendix1) to produce an output. Based on our experiment, we provide compelling evidence that transfer learning can be successfully applied when using the CNN architecture with datasets of limited volume. The transfer learning process involves discarding the last few layers of a pre-trained network and retraining new layers for the specific target task.

2.2 B. Domain knowledge

The available literature encompasses studies that examine the identification of plant diseases through the analysis of images containing various plant leaves. Within this field, two levels of knowledge generation coexist and eventually merge. The first level comprises research that addresses the identification of plant leaf diseases using two approaches: extracting leaf shape characteristics [60], [11] and extracting texture characteristics (such as inertia, homogeneity, and correlation obtained through calculating the co-occurrence matrix of the image's gray levels) [60], combined with color extraction [35]. Specifically, color extraction enables the identification of plants based on soil type [19], while textural and shape properties facilitate the identification of plants based on their leaves [1]. In other words, plants can be classified by considering information about leaf color and texture [63], [30], [81]. A subsequent level of knowledge emerges, focusing on identifying the most effective techniques and methods in artificial intelligence for extracting image characteristics of living organisms, including humans, animals, and plants. Our attention is specifically drawn to the results of studies [4] that identify leaf species, pests, or diseases to generate automated remedial solutions; [83] that detect diseased areas on leaves while striving to enhance the accuracy of their techniques; [67] that detect and differentiate plant diseases based on type and disease stage, achieving classification accuracies ranging from 65% to 90%. Additionally, [22], [40] develop a technique that combines characteristic extraction with neural network assembly for recognizing plant diseases, resulting in improved generalization of learning capacity. A technique has been developed, as described in [3], for automatically detecting and classifying plant diseases using an Artificial Neural Network (ANN). The technique analyzes leaf images and assigns plants to specific disease groups based on their characteristics. Our study combines this approach with deep learning to create a visual diagnosis method specifically for identifying vine diseases. The methodology draws upon previous research: [75] explored deep learning for plant disease recognition in leaf images, [6] developed a CNN-based algorithm for detecting and classifying symptoms in tomato leaves (SDCT), [42] focused on plant disease classification using k-Means algorithms or semi-automatic techniques (KCM), which were further extended by [78] and [23], who developed a deep system for assessing disease intensity using CNNs [12], [23]. In [11] and [39], theoretical and practical arguments are presented highlighting the advantages of CNNs, such as automatic feature extraction from raw images. Based on this knowledge, we developed a recognition method by employing deep CNNs, which we explain in the subsequent sections. Furthermore, considering our expertise in deep neural networks and agriculture, we recognized the need for more complex and novel approaches to extract and classify plant characteristics effectively. The technique for detecting and classifying leaves relies on extracting color characteristics from the leaf images as its foundation.

3 Research methodology

The research methodology aligns with an experimental approach based on scenarios. Initially, an end-to-end convolutional neural network (CNN) model was tested on a specific dataset [66]. Subsequently, the initial scenario was refined using insights from the literature by fine-tuning pre-trained CNN models trained on the ImageNet database, specifically MobileNetV2 [82]. Based on this, the approach involved extracting features from the pre-trained networks and applying three traditional classification algorithms to these features. This method significantly reduces the training time required for deep learning algorithms and achieves high accuracy. New information discovery is facilitated through techniques such as discovery techniques [51] or a implemented model [72], which can recognize a wide range of predefined characteristics [9], including the use of unsupervised clustering [47].The research builds upon previous work in plant and leaf identification using deep learning, as documented in studies such as [21] and [69]. These studies emphasize the challenge of detailed recognition of various objects, including plants, in large-scale visual recognition systems [69]. Based on these findings, the research methodology was designed to focus on CNN-based active learning for the recognition and classification of vine leaves. The theoretical approaches discussed in specialized literature [56], [28],[13] were considered during the methodology design phase. These approaches suggest that, when employing transfer learning, it is important to address three key questions: What is transferred? How to transfer? When to transfer? In addition, inspired by [28], the question of Where is knowledge transferred? was also included to elucidate the role of knowledge delivery in relation to user profiles and/or the technology employed. Addressing these questions aided in conceptualizing a practical prototype for extracting the necessary/useful knowledge base for active learning in the domain of living organisms (humans, animals, and plants) through image-based learning, either by generating new knowledge or enhancing existing knowledge [56]. Finally, the classification of vine diseases and the generation of lessons learned were conducted using the Deep Convolutional Neural Network (CNNs) algorithm as part of the research script.

4 The practical model of extracting the knowledge base through discovery

The practical model we have developed, which extracts knowledge through discovery, is based on existing literature [7], [50], [55], [24]. It focuses on active learning for the recognition and classification of CNN-based vine leaves. These leaves are categorized into different groups, including healthy leaves, leaves affected by grape mildew, grape black measles, grape leaf blight, and grape black rot. The goal of the experiment is to achieve high classification accuracy for these leaves based on the available images within a short timeframe. To accomplish this, five sets of images representing the different leaf categories were compiled and utilized for training subsequent classification algorithms. The practical model was designed with multiple scenarios centered around algorithms that extract information through discovery during the training process, employing the transfer learning technique (active learning). In our research, we adopted the freezing scenario within the transfer learning strategy to enhance the accuracy and efficiency of the training process. As the main classification engine, we chose EfficientNet, which is a recently developed family of deep neural networks. EfficientNet is built on the principle of balancing network depth, width, and resolution to achieve improved performance. The family of models, proposed by [50], employs a scaling method that uniformly scales the depth, width, and resolution dimensions of a CNN using a compound coefficient,ϕ, which proves to be highly effective. EfficientNet utilizes the Swish activation function instead of the Rectifier Linear Unit (ReLU) activation function. The EfficientNet group comprises 8 models ranging from B0 to B7. The structure of EfficientNet incorporates the inverted bottleneck MBConv from MobileNetV2 [70], resulting in a reduction in calculation volume by a factor of k^2, where k represents the kernel size or the width and height of the 2D convolution window [80]. The effectiveness of this approach has been demonstrated by scaling up MobileNets and ResNet. EfficientNet-B7 achieves state-of-the-art performance with 84.3% top-1 accuracy on ImageNet, while being 8.4 times smaller and 6.1 times faster during inference compared to the best existing ConvNet. EfficientNets also demonstrate successful transfer learning and achieve state-of-the-art accuracy on datasets such as CIFAR-100 (91.7%) and Flowers (98.8%), requiring significantly fewer parameters compared to other models.

4.1 A. Description dataset

In this research, we explored the utilization of the EfficientNet, InceptionV3, and ResNet50 deep learning architectures through transfer learning to achieve accurate classification. The performance of the classification approach was validated on an extensive dataset comprising numerous leaf images categorized into five distinct classes. The dataset consisted of 7,357 training images and 1,879 testing images. The images were collected from both public datasets, such as Plant Village, and experimental fields. To enhance the dataset, image enhancement techniques were applied, resulting in a dataset of 9,236 images. The dataset used for generating and evaluating the proposed model included images from five classes: healthy leaves (1,693 samples), leaves infected with black rot (1,920 samples), leaves infected with black measles (1,920 samples), leaves infected with blight (1,722 samples), and leaves infected with downy mildew (102 samples). The images were divided into a training dataset (7,355 samples) and a test dataset (1,878 samples). The original images in the dataset were RGB images of various sizes. As part of the image pre-processing stage, all the images were resized to a specific input size required by the considered networks, and image quality was improved. The rescaled images were utilized during model optimization and prediction. To address the issue of overfitting that can arise when training a large number of parameters, we employed two methods of expanding the input dataset: data augmentation. Various techniques such as rotation, flipping, shearing, zooming, and color changes were randomly applied during the training stage to minimize the risk of overfitting.

Figure 1: Leaves belonging to the 5 classes in relation to which the classification is performed

4.2 B. Model architecture

Various CNN-based transfer learning architectures, such as EfficientNet, InceptionV3, and ResNet50, were employed to diagnose diseased leaves in a dataset consisting of both diseased and healthy vine leaves. Each architecture was enhanced with additional layers, including an activation layer, batch-normalization layer, and dropout layer. The parameters of the architectures, such as dropout values, learning rates, and batch sizes, were tested to achieve optimal accuracy and efficiency in classification.

4.3 C. Experimental Setup

The experiments were conducted on a MacBook Pro 13.3" with an M1 processor, featuring an 8-Core CPU, 8-Core GPU, 16GB UM, and 1TB SSD. The codes were implemented using the Keras library, which is a Python-based deep neural network library trained on the ImageNet dataset. The overall accuracy (OA) and standard deviation (STD) of five tests were used to present the results for each dataset. Table 1-2 provides an overview of the main parameters used in all experiments. Augmentation techniques were applied using the ImageDataGenerator method. To construct our own classification layer stack on top of the EfficientNet, InceptionV3, and ResNet50 architectures, we utilized GlobalMaxPooling2D to convert the 4D tensor into a 2D tensor with dimensions (batch size, channels). This significantly reduced the number of parameters. The BatchNormalization layers were frozen to maintain the mean and variance of the inputs during training. For regularization, a Dropout layer was added before the classification layer with a dropout rate of 50% to mitigate overfitting. We also experimented with a dropout parameter value of 0.2 [24] and analyzed its impact on classification performance. EfficientNet, InceptionV3, and ResNet50 were treated as feature extractors within the transfer learning workflow. ReLU was used as the activation function, except for the last dense layer, where SoftMax was selected. The output layer consisted of 5 nodes corresponding to the different classes. Two data generators were created, one for training data and another for testing data, to load the data from the source file. The dataset comprised labeled folders containing images, and the path to this folder was included in the script file. To expedite learning, the batch size for batch normalization was set to 32, and all experiments were run for 10 epochs. The Adam optimizer was utilized for training the networks, with categorical cross-entropy as the loss function and a learning rate of 0.001 [50]. Thus, our approach significantly reduces the training time typically associated with deep learning algorithms when starting from scratch while achieving high accuracy.

The training images were of varying sizes: a) Color images of size 224x224 were trained. Implementation involved using pre-trained weights from the ImageNet dataset, with a dropout value of 0.5, learning rate of 0.001, and batch size of 32. b) Color images of size 240x240 were trained. Implementation involved using pre-trained weights from the ImageNet dataset, with a dropout value of 0.5, learning rate of 0.001, and batch size of 32. c) For cases a) and b), the EfficientNet architectures (B0, B1, B2, B3, B4, B5, B6, B7), as well as InceptionV3 and ResNet50, were applied to identify leaves affected by 4 different vine diseases or healthy leaves. In the transfer learning process, several standard layers were replaced with new layers, including a fully connected layer and a Softmax classification layer, with the number of classes set to 5. The trained models were evaluated for accuracy and total

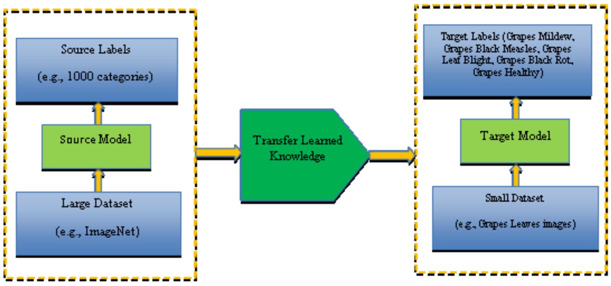

Figure 2: Transfer Learning Structure Steps

execution time using a set of test images. After the training and testing stages, the most efficient algorithm was selected based on criteria such as high classification accuracy, low execution speed, and relative picture size. To improve algorithm performance, they were tested on multiple sets of labeled images. If misclassifications were found, those images were added to the training files to enhance the learning process.

4.4 D. Performance metrics

In this study, a multi-class classification process was performed to distinguish vine leaves affected by 4 types of diseases from healthy ones, resulting in 5 categories. Due to unbalanced data, precision, recall, and F1-score were applied as metrics to evaluate classification performance. The metrics were calculated using the $TruePositive(TP)$, $FalsePositive(FP)$, $TrueNegative(TN)$, and $FalseNegative(FN)$ indices. TP represents the number of correctly classified images for each disease, while FP denotes the total number of incorrectly classified images in all other categories except the relevant one. TN represents the correctly classified images in all other categories except the relevant one, and FN indicates the number of images incorrectly classified in the considered category. Precision measures the proportion of predicted positives that are actually positives, calculated as $PrecisionScore(PS) = TP/(FP + TP)$. Recall reveals the proportion of actual positives correctly classified, calculated as $RecallScore(RS) = TP/(FN + TP)$. F1-score provides a balance between precision and recall and is calculated as the harmonic mean of precision and recall scores, $F1 = 2 * PS * RS/(PS + RS)$[49].

4.5 E. Experiment results

Tables (Tab11). and (Tab2 2) in Appedinx 2 present a comparative analysis of the performance of implemented architectures using different parameters (precision, recall, F1-score) and the total training time in seconds. The ResNet50 algorithm achieves the highest success rate in the classification process for both 224x224x3 images (precision-99.042%, recall-96.166%, F1-score-99.047%) and 240x240x3 images (precision-99.202%, recall-96.201%, F1-score-99.201%). The training time for ResNet50 is 7257 seconds and 8245 seconds, respectively. The EfficientNetB2 algorithm ranks second in efficiency, with shorter training times of 4588 seconds for 224x224x3 images and 5435 seconds for 240x240x3 images compared to ResNet50. The EfficientNetB0 algorithm ranks third in classification accuracy but performs best in terms of training time, with 3727 seconds for 224x224x3 images and 3957 seconds for 240x240x3 images. The decrease in training time is influenced by the reduction in the number of parameters between algorithms. The evolution of estimation accuracy during 10 epochs for both 224x224x3 and 240x240x3 images is shown in Figures (Fig5 4) and (see Fig6 **??**) in Appendix 3. Figure 7 (see Fig7 5) in Appendix 3 illustrates the comparative training time for the algorithms in scenarios I and II. The InceptionV3 algorithm trains the fastest in both scenarios, demonstrating computational efficiency in terms of generated parameters and economic costs. However, InceptionV3 also has the lowest efficiency. Figure 8 in Appendix 3 (see Fig8 6) displays the precision of classification in relation to different dropout parameter values for EfficientNetB2, InceptionV3, and ResNet50 architectures. There is a slight increase in classification precision parallel to network training time (see Fig9 7 Appendix 3). Different learning rate settings of 0.01 [49] and 0.001 [38], [35] were considered, but they resulted in decreased classification accuracy for all analyzed architectures, despite reduced training time. The CNN-based classification architectures explored in this study, using transfer learning, achieve high accuracies: 99.202% for ResNet50, 98.978% for EfficientNetB2, and 98.732% for EfficientNetB0. These accuracies are comparable to other implemented methods for classifying diseased leaves, such as UnitedModel (98.57% [39]) and DICNN Model (97.22% [50]). These architectures prove to be effective tools for farmers in decision-making, as they can help control losses due to disease, increase production, and reduce pesticide use. The evaluation dataset includes images of leaves affected by 4 disease categories and a category of healthy leaves. The dataset can be expanded by adding images from a broader vineyard area with a greater variety of vine-specific diseases. Additionally, the database can be enriched with images captured by drones. The architectures' performance was tested on a single database, but they can be evaluated using images from multiple databases representing different crops and geographical regions to ensure real-time disease identification. Maintaining high performance during real-time image processing is crucial. Establishing a correlation between disease onset, identified through pictures, and climatic factors (atmospheric temperature and humidity at the leaf level) is a planned future work.

5 Discussions

The identification of plant diseases using advanced and intelligent techniques is a topic explored in computer science, agriculture, and economics [51], [52], [12], [40]. We have developed a practical model that addresses this problem through various scenarios, where the primary focus is on learning through transfer learning using the CNNs (Deep Convolutional Neural Network) approach. This approach has yielded significant findings in response to the research questions stated in the introduction. Our scenarios primarily revolve around comparison and classification accuracy (CA). The obtained results further reinforce the findings from [43], specifically highlighting the impact of transfer learning on classification accuracy and the superiority of transfer learning approaches over end-to-end models for benchmarking datasets. It is also evident that datasets with fewer data points exhibit a noticeable performance advantage. Our experimental studies are subject to potential threats to validity [8]. To ensure internal validity, we have not solely relied on one transfer learning approach; instead, we have designed and implemented multiple transfer learning scenarios as active discovery learning for model benchmarking. While we have covered several transfer learning scenarios and focused on deep learning rather than traditional machine learning patterns, we acknowledge that knowledge acquisition through discovery from the plant classification process, based on prepared deep learning models, is attainable. In terms of external validity, our conclusions hold true for the datasets described in the paper, and our observations represent discoveries that could be validated by testing a new dataset within the same plant category or even in humans. The results obtained align with [79], which emphasizes that the quality and size of the images play a crucial role. As for construct validity, our experiments were conducted on widely used datasets that are still employed by other researchers in this field. The validity of the conclusion addresses threats that may impact the ability to draw appropriate conclusions. We divided the available data into training and test datasets using the widely accepted ratio (70-30%) and utilized five-fold cross-validation during deep learning experiments. These validation techniques were employed to mitigate the impact of randomness in the data. The results were reported based on the accuracy parameter. Thus, the first research hypothesis has been confirmed, highlighting that the classification of plants can benefit from knowledge transfer in deep learning, thereby facilitating the development of automatic plant identification systems, particularly for vine leaves. The second research hypothesis has also been validated based on the learning scenario obtained and presented in the previous sections. This learning scenario, enabled by knowledge transfer, enhances the performance of plant classification models through automatic identification systems in deep learning, resulting in knowledge generation about plants by studying vine leaves and classifying them as healthy or unhealthy. Experimental results indicate that the proposed approach is valuable, significantly aiding in the accurate detection of leaf diseases with relatively minimal computational effort. This paper presents a solution in the field of agricultural plant disease detection [26], [27], supporting the implementation of appropriate treatments, which are crucial for the economic growth of predominantly agrarian countries. Specifically, the proposed technique initially identifies the leaf region using color characteristics extracted from leaf images [47], based on a mixture model that precisely locates the affected region on the leaf surface. The literature [27], [48] does not explicitly mention the existence of commercial solutions based on our research, apart from those focusing on plant species recognition based on leaf images. Recognition systems are valuable in developing smart agriculture guides, contributing to the automation of agriculture and forestry, biodiversity conservation, ecological monitoring, and serving as educational tools that showcase representative agricultural practices [38]. The recognition of plants becomes vital due to the fact that many species serve as raw materials for medical, cosmetic, pharmaceutical, or chemical industries, necessitating continuous and accurate identification and classification [18].

6 Conclusion

The correct classification of species of living organisms (human beings, animals and plants) exemplified by plants in the case of this study has many advantages not only here but in a few other areas, for example, studies on biodiversity, health and forests. Instead of manual plant processing by experts, automated plant identification systems allow stakeholders to quickly cope with the huge amount of plants and reduce the time and cost of these operations. This paper contributes information, learning through transfer learning that we perceive as active learning that generated discovery using deep learning algorithms for classifying plants on multiple transfer-through learning scenarios for deep learning models. The study demonstrated that transfer learning improves the performance of deep learning models and especially of models in which by applying deep functions and using fine tuning to provide better performance compared to other transfer learning strategies. This result implies that instead of applying only one end-to-end CNN model for mass classification, the other transfer learning approaches considered in the case of low-precision performance must also be taken into account [5]. The limitations of the research converge from, the results obtained, should be compared with other results. Comparing our results with other methods of detecting diseases in leaf images, will facilitate the choice of the most optimal method of generating results according to them [85], [68], [3]. Moreover, they fall within the scope of limitations in the specialized literature, more precisely they are part of the research that can be regarded as attempts that reside in the isolated application of the systems, with direct effects arising from the lack of undertaking of any systematic effort to reuse and facilitate the transfer of knowledge to other applications, respectively the non-exploitation of learning transfer (TL) to capitalize on the performance and efficiency of the systems for recognizing the activity of live organisms. In this work, a new approach to the use of the deep learning method to automatically classify and detect plant diseases from images of leaves was explored. The developed model was able to detect the presence of categories of leaves and distinguish between healthy leaves from diseased ones. The complete procedure was described, from collecting images used for training and validation to pre-processing and augmenting images and, ultimately, CNN's deep training and fine-tuning procedure. Various tests have been carried out to verify the performance of the newly created model. An extension of this study will be the collection of images to enrich the database and improve the accuracy of the model using various techniques of fine-tuning and augmentation. Furthermore, further work will involve spreading the use of the model by training it for the recognition of plant diseases over wider terrestrial areas, combining aerial photographs of drone-captured vineyards and convolution neural networks (CNN) for object detection. Another extension of this work will focus on the development of hybrid algorithms such as genetic algorithms and NNNs to increase the recognition rate of the final classification process highlighting the advantages of hybrid algorithms; we will also make our future work dedicated to the automatic estimation of the severity of the disease detected. By extending this research, the authors hope to achieve a valuable impact on sustainable development, affecting the quality of crops for future generations.

7 Appendix 1

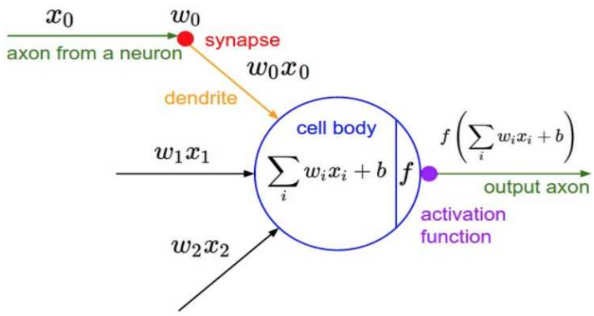

Figure 3: Mathematical modeling of the biological neuron cite(https://cs231n.github.io/neural-networks-1/)

8 Appendix 2

Table 1: RESULTS SCENARIO 1 – IMAGES OF SIZE 224x224x3

No	Architecture Model	Precision (%)	Recall (%)	F1score(%)	Image Size	Total training Time/sec	Trainable params.
1	EfficientNetB0	98.732	98.722	98.701	224x224x3	3727	1,319,429
2	EfficientNetB1	98.593	98.562	98.570	224x224x3	4187	1,319,429
3	EfficientNetB2	98.835	98.829	98.831	224x224x3	4588	1,450,757
4	EfficientNetB3	98.238	98.243	98.209	224x224x3	5288	1,582,085
5	EfficientNetB4	98.680	98.669	98.634	224x224x3	7716	1,844,741
6	EfficientNetB5	98.199	98.190	98.180	224x224x3	10712	2,107,397
7	EfficientNetB6	97.684	97.657	97.652	224x224x3	214581	2,370,053
8	EfficientNetB7	97.730	97.710	97.704	224x224x3	18942	2,632,709
9	InceptionV3	79.110	77.956	77.632	224x224x3	3391	2,107,397
10	ResNet50	99.042	99.065	99.047	224x224x3	7257	2,107,397

Table 2: RESULTS SCENARIO 2 – IMAGES OF SIZE 224x224x3

No	Architecture Model	Precision (%)	Recall (%)	F1-score (%)	Image Size	Total training Time/sec	Trainable params.
1	EfficientNetB0	98.606	98.616	98.540	240x240x3	3957	1,319,429
2	EfficientNetB1	98.676	98.669	98.632	240x240x3	4868	1,319,429
3	EfficientNetB2	98.978	98.988	98.981	240x240x3	5435	1,450,757
4	EfficientNetB3	96.305	96.166	95.966	240x240x3	6790	1,582,085
5	EfficientNetB4	98.551	98.562	98.537	240x240x3	8785	1,844,741
6	EfficientNetB5	97.960	97.604	97.709	240x240x3	12626	2,107,397
7	EfficientNetB6	98.186	98.190	98.183	240x240x3	15676	2,370,053
8	EfficientNetB7	98.551	98.509	98.525	240x240x3	21306	2,632,709
9	InceptionV3	80.200	78.914	78.506	240x240x3	3942	2,107,397
10	ResNet50	99.202	99.201	99.201	240x240x3	8245	2,107,397

9 Appendix 3

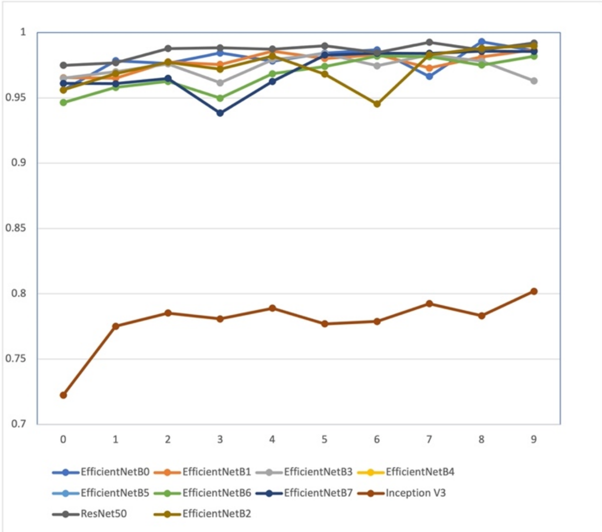

Figure 4: Evolution of classification accuracy over 10 epochs in the case of architectures analyzed on images of size 224x224x3

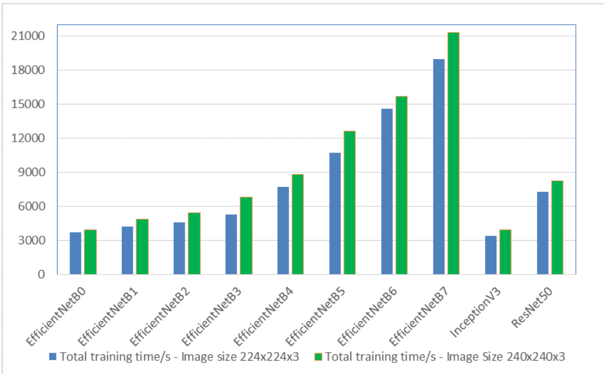

Figure 5: The training time recorded in the case of the architectures considered illustrated comparatively on the two sets of images of dimensions 224x224x3 respectively 240x240x3

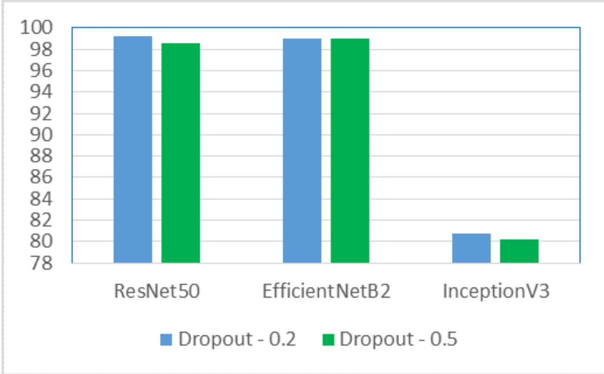

Figure 6: Precision classification with different dropout values

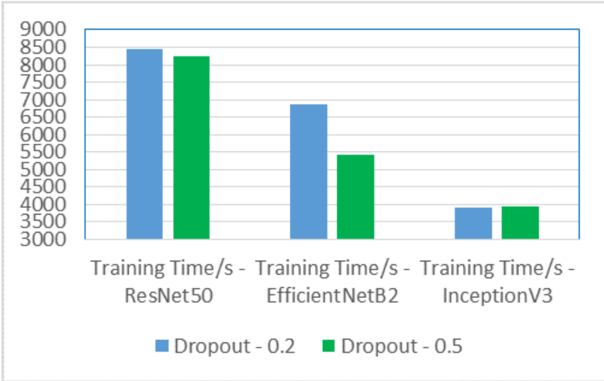

Figure 7: Training Time/s with different dropout values

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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