Deep Learning in Grapevine Leaves Varieties Classification Based on Dense Convolutional Network

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***Abstract*—Grapevine leaves are utilized worldwide in a vast range of traditional cuisines. As their price and flavor differ from kind to kind, recognizing various species of grapevine leaves is becoming an essential task. In addition, the differentiation between grapevine leaf types by human sense is difficult and time-consuming. Thus, building a machine learning model to automate the grapevine leaf classification is highly beneficial. Therefore, this is the primary focus of this work. This paper uses a CNN-based model to classify grape leaves by adapting DenseNet201. This study investigates the impact of layer freezing on the performance of DenseNet201 throughout the fine-tuning process. This work used a public dataset consist of 500 images with 5 different classes (100 images per class). Several data augmentation methods used to expand the training set. The proposed CNN model, named DenseNet-30, outperformed the existing grape leaf classification work that the dataset borrowed from by achieving 98% overall accuracy.**

***Keywords*—grapevine leaves varieties, pre-trained CNN, fine-tuning, layer freezing, DenseNet201**

I. INTRODUCTION

Leaf identification is an interesting and challenging research field due to the variety of species. Leaves are commonly used to identify a plant, as they contain a significant variation of data that is available in botanical reference collections and are the easiest to obtain in field studies. Plant leaves are more appropriate for classification because they contain plant-specific characteristics [1]. Many scientists have proposed various automated techniques for identifying leaves in order to create an application that can help ordinary people identify plants based on a leaf or detect a specific disease revealed by the leaves. Few studies have been implemented to classify the leaf species of the same plants, and it is difficult to classify them because their characteristics are so similar. As a result, the majority of research has concentrated on various plant species and disease classifications. However, machine learning and deep learning approaches to plant leaf classification have recently gained popularity. These techniques can be improved for anomaly classification, ensuring early leaf classification, and producing a better, more accurate result.

Grapevine leaves, for example, are used in a variety of famous cuisines in Greece, Turkey, Iraq, and other Middle Eastern countries [2]. Grapevine leaves can be used fresh in the spring for cooking, usually wrapped around rice, or stored in various ways for use in other seasons. Grapevine leaves are classified into several types based on their shape, size, and leaf edge. Unfortunately, not all of them are suitable for cooking. The characteristics of the grapevine leaves are used to classify them with the most economic value through these characteristics and the separation of consumable grapevine leaves based on quality. The separation of varieties is done by visual inspection, usually by agronomists, which requires expert knowledge because it is so hard to distinguish visually. Therefore, automating this process is highly beneficial.

Because the characteristics of grapevine leaf species are so similar, one of the first steps in automatic grapevine leaf classification is to find a high-quality dataset. As a result, a few studies on grapevine leaf classification have been conducted. The study conducted in [3] is one of the most recent studies to distinguish different grape leaf species from the same group in grape leaf research. They gathered a dataset of 500 images of vine leaves from five different classes, captured with a special self-illuminating system. This study makes use of it because of its high-quality data. Previous research reduced the dimension of the features before classifying the images, resulting in a decrease in classification accuracy. However, the drawback of SVM is that it cannot differentiate between leaves that have almost the same shape. DenseNet201 was modified in this work to create a precise CNN model for classifying vine leaves in order to improve accuracy. Adapting the DenseNet architecture to build an accurate model entails several approaches, including investigating fine tuning to determine the appropriate number of layers and exploring the best optimization function. Furthermore, various methods are used to expand the dataset and obtain enough training samples. Image transformations based on

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geometry are used, such as flipping, rotation, cropping, and color correction.

The remaining sections of this paper are organized as follows: Section II includes the literature review. The materials and methods are detailed in Section III. Section IV discusses the experimental results in depth. Section V provides a conclusion followed by a discussion on future suggestions.

II. Literature Review

Many scientific researchers have proposed various techniques in recent years to identify plants based on a leaf or detect a specific disease revealed on the leaves. Deep learning has recently been developed and achieved outstanding computer vision results. A Convolutional Neural Network (CNN) is a deep artificial neural network that uses image visualization to perform image classification, similarity grouping, and object detection [4]. The studies in [5, 6] used deep learning approaches to identify plant leaves. Narong [5] proposed a method for extracting geometric features from leaf images. In that paper, Artificial Neural Networks (ANN) used as a classification method.

Furthermore, they used a dataset for designing their model, which contained 8 species of herb leaves and 400 leaf images. They achieved an overall accuracy of 90.50%. Moreover, Temsiririrkkul *et al.* [6] proposed a technique for identifying plants based on their leaves with similar morphological characteristics. They used three common pre-trained state-of-the-art CNN architectures as transfer learning on their dataset, and the highest result achieved by VGG-16, ResNet-50, and InceptionV3 was an accuracy of 98.71%, 91.32%, and 98.17%, respectively.

However, several deep learning models were used to identify leaf diseases. Wu *et al.* [7] proposed a method to use Region of Interest (ROI) as input images, and key-point features were extracted using the Scale-Invariant Feature Transform (SIFT) algorithm. Then, a bag of words is coded using these key-point features, and the classification is accomplished using the SVM method. They achieved an accuracy of 92.13%. Malik *et al.* [8] used a hybrid model that employed deep learning approaches to recognize and classify sunflower leave diseases. VGG-16 and MobileNet architectures are combined as an ensemble learning strategy and then utilized for classification purposes. They achieved an accuracy of 89.2%.

The study in [9] used ResNet50 as a feature extraction method and SVM as a classifier. Hence, by combining ResNet50 and SVM, they reached an F1 score of 98.38%. Besides, Liu *et al.* [10] proposed a CNN model for identifying grape leaf diseases. To overcome the overfitting issue and reduce the number of parameters, they used a depthwise-separable convolutional layer instead of a standard convolutional layer. As a result, their proposed CNN model outperformed standard ResNet and GoogLeNet architectures in terms of efficiency and accuracy. The study obtained an accuracy of 97.22%. Furthermore, a comparison study of healthy and unhealthy grapevine leaves was carried out in [11]. A laboratory hyperspectral imaging system is set up to analyze individual leaves collected in the greenhouse. Then, the extracted mean leaf spectra are evaluated using a modified Support Vector Machine (SVM) classifier. The study achieved an F1 score of 93.19% and 98.57% for a multiclass and binary classification, respectively.

Recently, some studies have been proposed to classify grapevine leaf diseases. Hasan *et al.* [12] used a CNN with a learning rate of 0.0001 to classify grapevine leaf diseases and achieved an accuracy of 91.37%. The study in [13] proposed an enhanced VGG16 approach to improve the accuracy of detecting 5 grape leaf diseases. The accuracy of the proposed system was compared to VGG16 with fully connected layers and VGG16 with an SVM classifier. The proposed model outperformed others with an accuracy of 98.4%.

In contrast, Bharate *et al.* [14] provided a method that uses image processing techniques to classify grape leaves as healthy or unhealthy. Grape leaf features such as color and texture were extracted and input into KNN and SVM classifiers. The texture features contained properties of homogeneity, correlation, contrast, and energy. While the HSV color space was used to extract color features, the experimental results revealed that the performance of the two classifiers, KNN and SVM, was an accuracy of 90% and 96.6%, respectively.

Few studies have been conducted to classify the leaf species of the same plants, and it is difficult to classify them because their characteristics are so similar. As a result, the majority of the studies in the literature focused on different plant species and disease classifications. This study's dataset was obtained from the research proposed in [3]. They increased the number of the data samples to 2500 images after using a data augmentation method. Then, they proposed three different approaches for classifying images of grapevine leaves. A fine-tuned MobileNetv2 model is used to extract features, and various SVM kernels are used to classify these features. The dimension of the features is reduced with the Chi-Square method. The most successful SVM kernel was Cubic, which reached an accuracy of 97.60%.

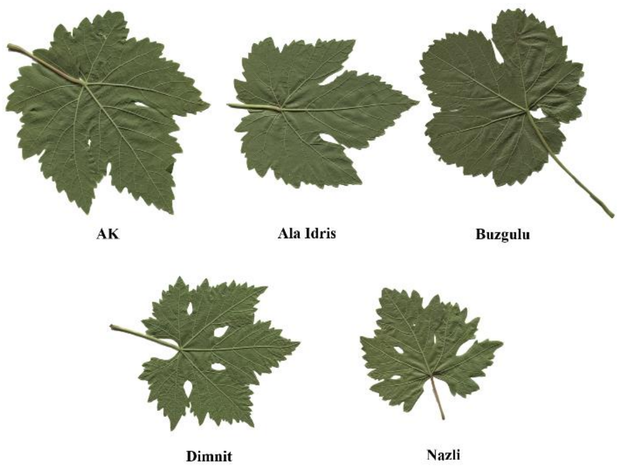

Figure 1. A sample for each grapevine leaf species.

III. Materials and Methods

A. Input Data Preparation

1) Dataset

In this study, the publicly available Grapevine Leaves Image dataset used, which is the Grapevine Leaves Image Dataset, which waacquired from [3]. This dataset consists of five species of grapevine leaves named “Ak”, “Ala Idris”, “Büzgülü”, “Dimnit” and “Nazli”. Each species contains 100 images of size 512×512 pixels. The total number of images used in this experiment is 500. These images were taken with a special self-illuminating system. Fig. 1 shows a sample of each species.

2) Data augmentation

A large number of data samples are required to classify images using deep learning approaches. Thus, the network design receives sufficient samples to generalize properly. Furthermore, different methods are used to expand the training set and achieve sufficient training samples. These techniques have a significant impact on improving the classifier’s results and performance while minimizing overfitting.

Geometrical-based image transformation, including flipping, rotation, cropping, and colour correction, is one of the most effective and easy-to-implement approaches [15, 16]. The adoption of these image augmentation techniques generates additional image samples and adds diversity to the dataset.

In this study, several augmentation methods used to expand the training set, such as horizontal flip, horizontal flip with sharp, vertical flip, vertical flip with sharpen, sharpen with random brightness contrast, and sharpen [17]. All operations of the augmentation on a sample image are shown in Fig. 2. Eventually, after implementing augmentation operations, the number of images in the training set is expanded to 2,800, and that is adequate to apply deep learning methods.

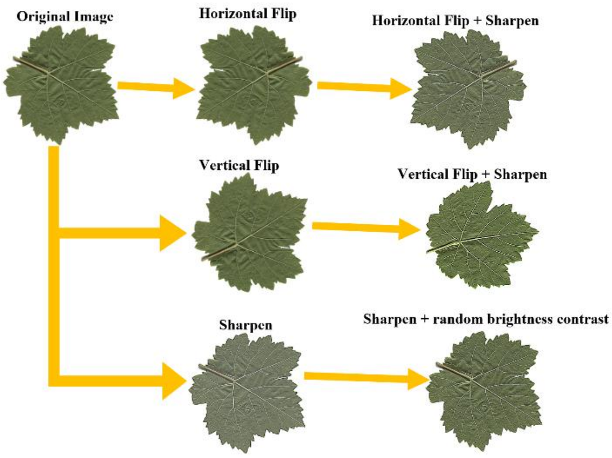

Figure 2. Illustrates the effects of each data augmentation approach on one sample of the dataset.

B. Fine-tuning Pre-trained CNN Models

A convolutional neural network consists of a large number of hyper-parameters. Therefore, designing a successful CNN architecture from scratch depends on finding a good combination between the hyperparameters, which is time-consuming and leads to trial and error [18]. In addition, training a CNN-based model from scratch requires a substantial quantity of training data. Since acquiring large-scale data collection is not always possible. Consequently, utilizing pre-trained CNNs is a prevalent practice in the research community to overcome the lack of data issue. Several state-of-the-art CNN architectures that designed for natural imaging and trained using one of the massive publicly accessible datasets, such as ImageNet. These architectures are then used as weight initializers to train new models on various datasets. This is known as transfer learning, and it occurs when the model applies what it has previously learned to a new field of study. The majority of widely distributed pre-trained CNNs were trained on image-based datasets. Consequently, images share many similar characteristics. Thus, pre-trained CNN methods proved their superiority over traditional CNN techniques [19]. DenseNet, ResNet, VGG, MobileNet, and Xception are among the most frequent pre-trained CNNs.

However, every field of study cannot benefit from the basic design of these networks. Fortunately, these CNNs were designed in a way that allows us to fine-tune them in an effort to overcome this deficiency. Fine-tuning can be accomplished in diverse aspects of the pre-trained CNNs, for instance, layer-freezing, dense layers, optimization methods, and learning rate. The most prominent practice is to freeze a number of subsequent layers, allowing the model to adapt to a new area of study. Therefore, multiple scenarios for fine-tuning should be explored for each target dataset in order to discover the optimal solution that fits the domain and prevents overfitting [20]. Since DenseNet201 is one of the most successful pre-trained CNN architectures. Thus, it was chosen to be explored in this study. The DenseNet architecture and its fine-tuning procedure will be covered in further detail in the subsequent section.

C. Adapting DenseNet201 for Grape Leaves Classification

A Dense Convolutional Network (DenseNet) [21] is one of the state-of-the-art CNN architectures that incorporates dense connections between the layers through Dense Blocks. DenseNet201 consists of 201 layers; each layer is connected to every other layer in a feed-forward manner. The vanishing-gradient problem is lowered, the feature propagation is strengthened, the feature reuse is encouraged, and the overall parameter count is greatly decreased. The DenseNet is based on the premise that convolutional networks can be trained to be significantly deeper, more exact, and much more effective if the connections between the layers close to the input and the layers near the output are much shorter. This was the study’s motivation for developing a model with DenseNet201: to achieve the best possible level of performance.

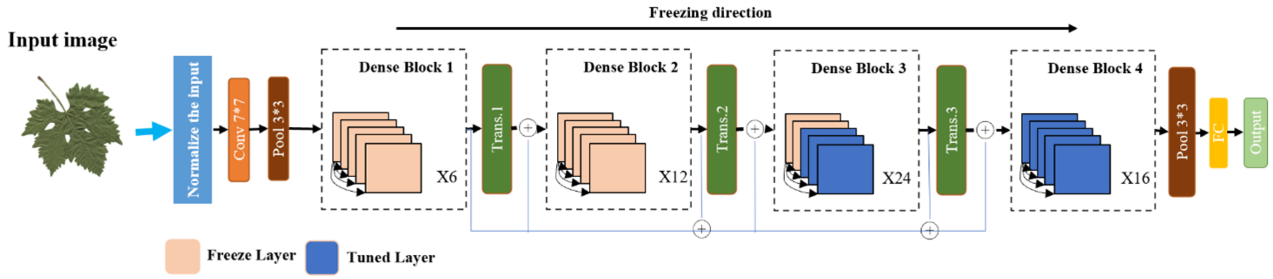

Figure 3. The framework of the proposed approach for designing the CNN model for grapevine leaves classification.

In addition, in three major scenarios, the potential for improving the network's overall architecture was investigated. First, freeze all layers of DenseNet201 and train the last fully-connected layer, which consists of 5 nodes, the number of classes in the dataset set. In other words, Densenet201 is used for feature extraction, and the last fully connected with SoftMax is used as a classifier. This scenario is named DenseNet-All. In the second scenario, all the layers of Densnet201 were trained on the dataset without layer freezing and using all of the network's previously learned weights. This method is named DenseNet-0. The third scenario aimed to determine the best number of freeze layers for training DenseNet201 on the dataset. Consequently, this method began by freezing five layers at the beginning of the architecture and progressively increasing the number of frozen layers. As the architecture progressed, the number of frozen layers increased by 5 every time. The process of adding five layers to the already-frozen ones while training the remaining layers continued until the first 70 layers froze. This indicates that 15 experiments were completed for this scenario, with each experiment labeled DenseNet-(number of frozen layers), as shown in Table I. However, as previously stated, layer freezing was discontinued at the 70th layer because the best results were obtained by freezing the first 15 and 30 layers, and freezing more layers did not result in an improved outcome. Fig. 3 shows the framework of using DenseNet for designing CNN model for grape leave classification.

IV. Experimental Results

DenseNet201, one of the most well-known pre-trained CNN networks, was investigated in this study. The mentioned model was trained using 500 images; more information can be found in the dataset section. The dataset has been divided into a training set of 80% and a testing set of 20%, and the training set has been expanded by using the mentioned data augmentation approaches. As a consequence, the training section of the dataset was expanded to 2,800 samples. That is, training the model on a larger number of data samples makes the model more generalizable.

Additionally, adjusting the DenseNet201 architecture was explored to further improve the model outcome. The primary fine-tuning strategy was focused on layer freezing, which was able to achieve the model's highest result. Table I details every achieved outcome in every of the four utilized metrics.

TABLE I. Details Every Achieved Outcome in Each of the Four Utilized Metrics

#	No. of freeze layers	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	DenseNet-All	2.00	14.00	2.00	12.00
2	DenseNet-0	97.00	97.39	97.00	97.07
3	DenseNet-5	94.00	95.38	94.00	94.20
4	DenseNet-10	92.00	92.29	92.00	91.99
5	DenseNet-15	**98.00**	**98.18**	**98.00**	**98.02**
6	DenseNet-20	96.00	96.13	96.00	96.00
7	Densenet-25	82.00	89.86	82.00	82.13
8	DenseNet-25	91.00	91.77	91.00	91.06
9	DenseNet-30	**98.00**	**98.18**	**98.00**	**98.02**
10	DenseNet-35	96.00	96.28	96.00	96.05
11	DenseNet-40	87.00	90.36	87.00	87.13
12	DenseNet-45	84.00	85.95	84.00	87.71
13	DenseNet-50	94.00	94.28	94.00	94.02
14	DenseNet-55	96.00	96.22	96.00	96.00
15	DenseNet-60	93.00	94.05	93.00	92.92
16	DenseNet-65	97.00	97.18	97.00	97.02
17	DenseNet-70	95.00	95.44	95.00	94.98

As shown in Table I, the performance of the model was evaluated on 100 test samples after each training session using four essential classification metrics: accuracy, precision, recall, and f1-score. In addition, each used metric is outlined in greater detail below.

- Accuracy measures how often the classifier predicts correctly. It can be defined as the ratio of correct predictions to the total number of predictions.
- Precision is defined as the number of true positives divided by the number of predicted positives.
- Recall is defined as the number of true positives divided by the total number of actual positives.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

- Where TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative respectively.
- F1-Score is the harmonic mean of precision and recall.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

Table I shows that the worst result was achieved with DenseNet-All, while the other scenarios obtained a remarkably better outcome. The top consequences were attained with DenseNet-15 and DenseNet-30, which is an accuracy of 98%. While, the model with the first 30 layers frozen (DenseNet-30) is preferable since the number of layers to be trained is smaller, which requires less time for training. Fig. 4 represents the confusion matrix of the top model result. It can correctly identify all test samples for three out of five classes, while its error rate for the remaining two classes is about 2%.

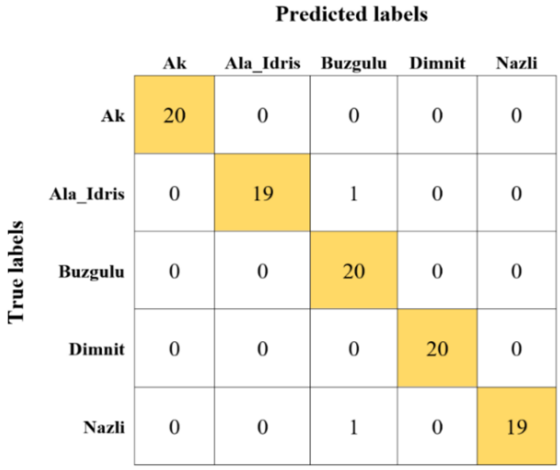

Figure 4. The confusion matrix of the highest achieved the result by DenseNet201.

Accordingly, the results demonstrated that utilizing DeseNet201 for feature extraction on the dataset is inefficient. While using pre-trained CNN models and investigating the number of freezing layers on the classification of grape leaves is an efficient methodology. The outcomes showed that the number of re-trained layers is a useful hyper-parameter that can be modified according to the available dataset.

TABLE II. THE HIGHEST ACHIEVED RESULT BY PROPOSED MODEL IN COMPARISON WITH THE BASE PAPER

#	Method	Precision	Recall	F1_score	Accuracy
1	**Proposed method**	**98%**	**98.18%**	**98%**	**98.02%**
2	Base paper method [3]	97.62%	97.60%	97.60%	97.60%

Finally, in order to evaluate the proposed model, a comparison of the best model obtained by the proposed methodology against the model proposed in [3] was performed, where they also collected the dataset and published it. Table II shows the highest achieved result by the proposed model in comparison with the mentioned paper.

The results show that the proposed model outperformed the original paper. They used the CNN model as a feature extractor, and their approach is staged, whereas this study method uses an end-to-end CNN model.

V. CONCLUSION

This work demonstrates significant progress in grapevine leaf species identification. According to the findings of this study, layer freezing is one of the most effective strategies, significantly impacting the outcomes. To begin, the DenseNet201 with the first 15 and 30 layers frozen attained the highest accuracy of 98%. The proposed model outperformed their achieved outcome by comparing this result to the base-paper result. This determines the superiority of fine-tuning approaches over the original methodology used in the literature. The obtained result, on the other hand, can be considered an outstanding achievement in the field. In the future, more fine-tuning strategies will be explored, such as experimenting with other optimization methods. Furthermore, the results will be compared to other CNN techniques, and the model will be validated using an external dataset.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Hunar Abubakir Ahmed conducted the research; Hersh Mustafa Hama and Shayan Ihsan Jalal wrote the paper; Mohammed Hussein Ahmed guided the research direction and revised the paper. All authors had approved the final version.

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