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Case Study

An efficient deep learning approach to help *Chenopodiaceae* biodiversity protection to prevent soil erosion (case study: Yazd province, Iran)

Ahmad Heidary-Sharifabad[a,*], Najma Soltani[a]

[a] *Department of Computer Engineering, Maybod Branch, Islamic Azad University, Maybod, Iran*

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A B S T R A C T

Background and objective: *Chenopodiaceae* species are important vegetation around the world, especially in the desert and semi-desert areas. Preserving the biodiversity of *Chenopodiaceae* species is crucial to preventing soil erosion. In addition, most of them are of ecological and economic importance and also play an important role in biodiversity around the world. Conservation of this biodiversity is vital to the survival and sustainability of the ecosystem. To protect plant biodiversity, it is essential to know the plant species in their natural habitats. Therefore, automatic identification of plant species in their habitat helps to analyze the species and thus take care of their biodiversity. Computer vision approaches can be used to automatically identify and classify plant species. Modern approaches use deep learning in computer vision.
Materials and methods: In this study, the ACHENY data set that consists of 27030 images of 30 species of *Chenopodiaceae* are used. Firstly, using the SuperPixel method, larger size images (448×448) than existing ACHENY dataset images size (224×224) are created. Secondly, based on the newly created dataset we introduce a proper deep learning model to identify *Chenopodiaceae* species.
Results and conclusion: The results of the evaluation confirm the improvement of the classification accuracy of ACHENY species by the proposed model compared to the previously presented models. The results of the experiments indicate a superiority of about 3% accuracy of the proposed method and all evaluation parameters of the research have increased to a reasonable extent.

1. Introduction

Soil is a valuable, non-renewable natural resource that is vital to the production of food, clothing, and other necessities of human life (Morgan, 2009). Soil is the main source of minerals necessary for the growth of organisms. Environmental conditions are not provided in the same way in all parts of the

* *Corresponding author.* Tel.: +98-35-3223-7329 .
E-mail address: ahmad.heidary@maybodiau.ac.ir , ORCID: 0000-0002-3356-4334
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earth, and therefore different plants grow in different places. Ecological factors such as climate, soil, and biological factors have a significant impact on plant growth. Therefore, it is necessary to identify the relationships between plants and the factors affecting their establishment and survival. Soil is one of the factors that is affected by vegetation and in contrast, soil also affects the properties of vegetation (Escudero et al., 2000). Changes in vegetation composition cause extensive changes in the soil. So that in a short time, returning to the original state is associated with limitations. In contrast, changes in soil conditions have led to changes in the composition of vegetation, which will not return to its original state until soil conditions return to normal (Ghane Ezabadi et al., 2021).

Soil erosion refers to the process by which soil particles are separated from their main bed and transported to another location by various factors such as wind, water, gravity, glaciers, and humans (Abedini & Toulabi, 2013). Soil erosion is mainly caused by natural currents of water and wind. This complex process may be accelerated by human activities such as vegetation destruction, deforestation, forest fires, and widespread urbanization (Jueyi et al., 2009; Onyando et al., 2005; Jamali et al., 2020). The soil is susceptible to erosion because the balance between soil erosion and production may be upset by anthropogenic activity (Stromsoe et al., 2016). Some natural soil conditions such as soil properties and topography can affect the process of soil erosion. Soil erosion is one of the main environmental concerns (Panagos et al., 2015). Soil erosion destroys plant and water diversity, destroys soil fertility, and reduces downstream water flow (García‐Ruiz et al., 2017). For soil conservation programs, preventing soil erosion is an essential practice (Vanmaercke et al., 2011). Prevention of soil erosion is one of the most important factors in the protection of natural resources.

An effective step in preventing soil erosion is to protect the effective vegetation in the surrounding areas. Since ancient times, plants were needed for satisfying human requirements such as shelter, food, medicine, and clothes (Ishnava et al., 2011). Due to plants' close relationship with the soil, the utilization of plants to protect soil is an important concern. For the survival of human and animal life, the life-supporting plant species must be concerned. The prerequisite for the life of these plants is to prevent soil erosion. Identifying and preserving plant species that prevent soil erosion is now a concern in the modern world. Vegetation plays an important role in hydrological processes and soil changes (Wei et al., 2007). Plant roots affect both the hydrological and mechanical properties of the soil (Cerdà et al., 2021). The most important effect of vegetation on the prevention of soil erosion is the soil stabilization by roots. The penetration of root fibers into the soil matrix is the cause of the mechanical effect. Root anatomy and the amount of root activity in different parts is an important factor in the amount of water absorption by the root. In plant-covered environments, precipitation first falls mainly on the vegetation and then is transferred to the soil through both litter falls and wash off (Huang et al., 2021; Wu et al., 2020).

Soil wind erosion usually occurs in arid and semi-arid regions (Mokhtari et al., 2021). Lands in vast deserts and plains that have no barrier or protection from the wind are exposed to severe wind erosion. The process of soil wind erosion occurs when the wind has considerable strength and speed and in addition, there is sensitive soil. This erosion is especially prevalent in areas with less vegetation because lack of vegetation is an aggravating factor of wind erosion. Land with good vegetation is almost safe from wind erosion. Vegetation in arid and semi-arid regions reduces wind speed at the soil surface and consequently reduces soil erosion. Shrubland can mitigate and control wind soil erosion. The effect of vegetation on wind erosion varies according to height, density, and type of vegetation. Vegetation prevents particles from moving in different ways. Therefore, the protection of vegetation in arid and semi-arid regions is of particular importance. Of course, the importance of protecting different plants is not the same due to their different effectiveness in controlling wind erosion (Hong et al., 2020).

Soil erosion usually occurs in areas that have been damaged by surface water flow. Rainfall with sufficient intensity and volume causes surface water flow. If the soil's resistance to corrosion is less than water flow power or the rainfall then primary soil segregates (Sharma et al., 2011). Generally, water erosion can be of different types, such as debris flow, streambank, gully, etc. (Alkharabsheh et al., 2013). Vegetation reduces soil erosion because it makes the soil surface less exposed to rain and surface water flow. Also, the presence of plant roots stabilizes the soil and absorbs some water. The presence of suitable vegetation reduces the speed of surface flows in the area and causes more water to penetrate the soil, so it has a significant effect on reducing soil erosion. Of course, different plants have different effects on reducing erosion because plants have different levels of coverage, and soil penetration and root volume are different. Soil erosion in the last century is often the result of indiscriminate vegetation destruction.

The complex array of anthropogenic disturbances such as urbanization, industrialization, road construction, military activities, over-grazing, over-collection of plants, and over-cutting were encountered directly affect plant species diversity. In the desert and semi-desert regions, the *Chenopodiaceae* family plants are worldwide. Considerable diversity of members of *Chenopodiaceae* family species, due to their tolerance of saline soil and subsoil conditions, are characteristic components of the vegetation of the arid and semi-arid area. This family is about 1500 species and 100 genera (Welsh et al., 2003). It is difficult for botanists to identify different species of this genus due to the lack of easily recognizable features, highly variable habitats, morphological differences between young plants and mature plants (Suchorukow, 2008). Many *Chenopodiaceae* species are characterized by arid and semiarid habitat requirements. In these areas, vegetation degradation often leads to soil erosion and habitat destruction. *Chenopodiaceae* species, especially in sandy soils, are of particular ecological significance. In the desert and sandy areas, the soil is always exposed to erosion due to flooding of severe winds, atmospheric precipitation, and the shortage of plants, bacteria, and other living organisms. In these soils, the most important factor that can prevent soil erosion is to stabilize soil particles, by the presence of *Chenopodiaceae* plants in these areas. These plants, with is roots, prevent the flow of sand and soil erosion (Casati et al., 1999).

Earth life is united by shared interests in the complex interactions between the environment and people, and ecological change. In matters of sustainability and long-term change, environmental history and world-systems history also have overlapping interests. The agricultural lifeways were sustained by the world over some long years, yet its environment has repeatedly degraded, indicating conceptual confusion between destruction and transformation (Butzer, 2005; Jäger et al., 2015). Soil erosion is a major problem, especially in arid and semi-arid regions of the world. This problem is very significant in a large part of the land because they are arid or semi-arid and their soil is not well covered. Vegetation has an important role in controlling soil erosion in arid and semi-arid regions and therefore its monitoring and protection are considered the most effective measure to control soil erosion (Hong et al., 2020). Therefore, it is necessary to conduct appropriate studies to protect the vegetation, which will lead to soil protection. This study highlights the automatic identification of plant species that prevent soil erosion and are ecologically important in arid and semi-arid regions. Therefore, automatic monitoring and protection of vegetation in vulnerable areas is recommended to prevent soil erosion. To do this, we use deep learning models to accurately predict plant species in their natural habitat.

Researchers in soil protection studies have paid less attention to the effectiveness of *Chenopodiaceae* plants in preventing soil erosion. However, some species of *Chenopediaceae* with their wide and deep roots have an effective role in preventing soil erosion, and their identification and protection in vulnerable areas are very important. Identification of *Chenopodiaceae* species in these areas can be done automatically by computer vision and using a suitable deep learning model. The aim of this study is to surveillance and identify plant species using deep learning models to protect them in vulnerable areas to prevent soil erosion. Therefore, in the continuation of this article, an efficient deep learning model for identifying *Chenopodiaceae* species is introduced and evaluated.

The rest of this paper organized as follows: In sub-section 1-1, the related works are reviewed briefly. In section 2, the materials and methods are described. ACHENY dataset details and basic concepts are explained in this section. Section 2 also includes the implementation and configuration of two proposed deep models for ACHENY classification. In section 3, the evaluation measures and experimental results obtained from two proposed deep models on ACHENY dataset are discussed. Finally, section 4 concludes our study and points towards future research directions.

1.1. Related works

Soil erosion has been managed in some parts of the world for about 70 years (Wen & Zhen, 2020). Although it is not possible to completely prevent soil erosion, it can be controlled to some extent by choosing appropriate strategies (Liu et al., 2011). To control soil erosion in these areas, engineering erosion control and biological erosion control methods have been widely used (Wen & Zhen, 2020). There is widespread research conducted to assess the effects of land cover types on soil erosion mitigation. Vegetation protection is one of the effective soil protection strategies (Heidary-Sharifabad et al., 2021b).

Accordingly, the assessment of soil erosion has become a very interesting topic (Wen & Zhen, 2020). To soil erosion assessments, machine learning (ML) models, such as random forest (RF), naive Bayes (NB), boosted regression trees (BRT), support vector machine (SVM) (Niazi et al., 2021), and artificial neural network (ANN) are known to be successful methods. In developing countries, soil erosion data are often incomplete, so ML models can be used to accurately predict vulnerable areas in soil erosion studies. Previous studies on soil erosion have focused mainly on evaluating the effects of soil erosion control practices (Chen et al., 2007; Fu et al., 2017; Xin et al., 2012; Zhao et al., 2013). To the best of our knowledge, previous studies have neglected methods/techniques for controlling soil erosion by identifying and preserving their effective vegetation. The aim of this study is to monitor and protect plant species in vulnerable areas using a deep learning model to prevent soil erosion.

2. Materials and methods

The study area includes desert and semi-desert areas of the Yazd province of Iran. The geographical coordinates of these areas are (longitude: 52° 45′ 56° 30′, latitude: 29° 48′ 33° 30′). The region was shown in the map of Normalized Difference Vegetation Index (NDVI) using Sentinel-2 images during summer 2021 (Fig. 1).

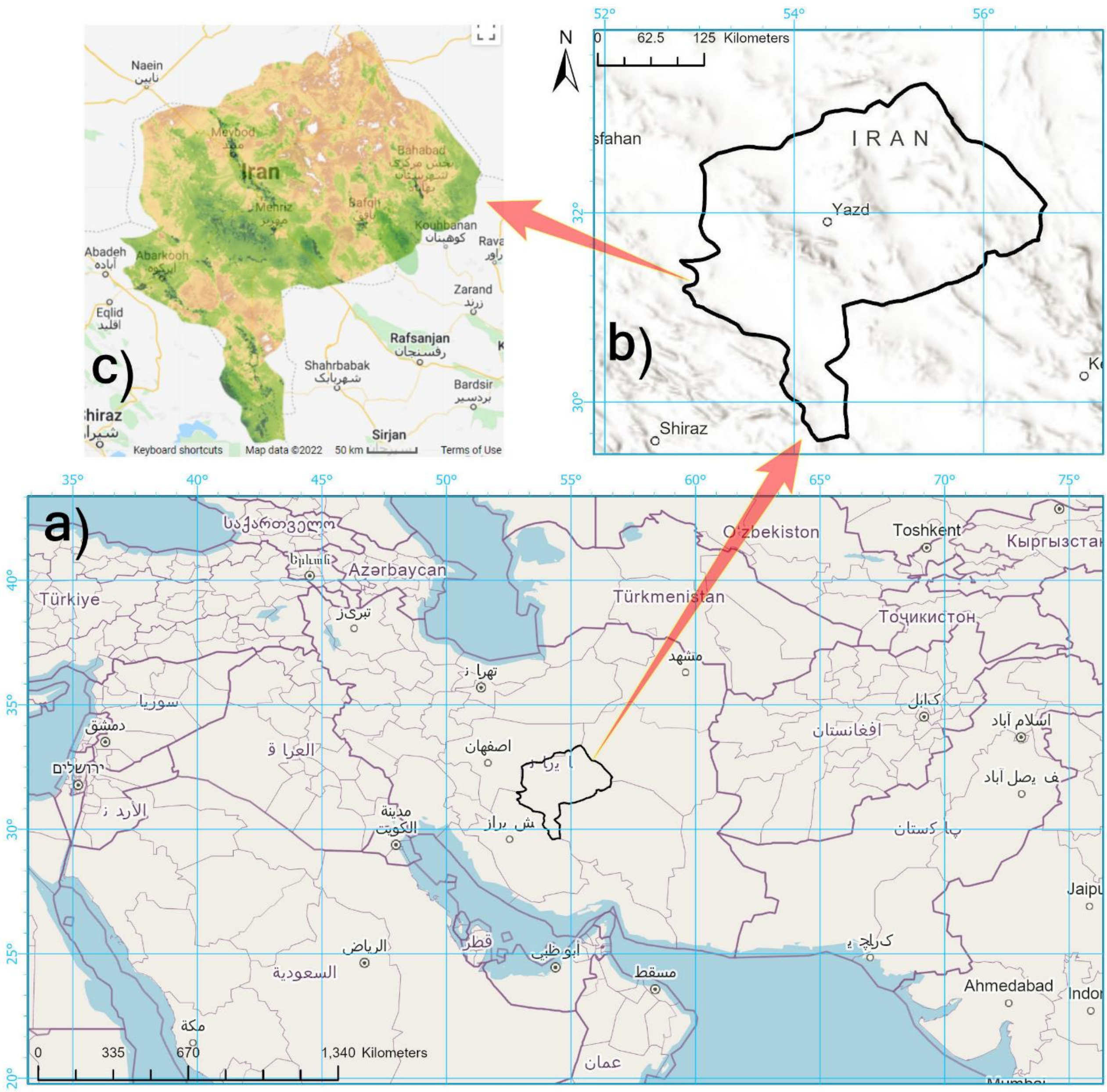

Fig. 1- (a) Yazd Province in Iran; (b) Yazd Province; (c) Normalized Difference Vegetation Index (NDVI) using Sentinel-2 images during summer 2021.

In recent decades, deep learning has been widely used in the field of computer vision and related methods have been studied and introduced (Heidary-Sharifabadet al., 2021a, 2021b). Convolution neural network (CNN) is a popular deep learning method in which multiple layers of artificial neural networks are trained to classify a set of images. In computer vision, the use of CNN to classify images has become commonplace because of its superior performance (Heidary-Sharifabad et al., 2021b). In this study, a suitable CNN model for the classification of the studied images is introduced.

Using a CNN model to classify specific images is possible if a related image dataset is available for model training. In this study, we used the ACHENY (Autumn *Chenopodiaceae* of Yazd) dataset (Heidary-Sharifabad et al., 2021c) for training our model. This dataset contains 27,030 images of 30 species of the *Chenopodiaceae* genus. These images have been made public in both 224×224 and 64×64 sizes. For further explanation, a sample image of each of the 30 species in the ACHENY dataset is illustrated in fig 1. The number of species images in this dataset is different. Detailed descriptions of this publicly available dataset are available at (Heidary-Sharifabad et al., 2021d).

In previous related research, the ACHENY database has been used without any modification. The innovation of this research is that, firstly, using the superpixel method (Shi et al., 2016), images with larger dimensions are created from the existing dataset. Secondly, we introduce a more accurate and larger CNN model and use the newly created data set for it. Superpixels are used as an interface between pixel-level processing and other image processing, leading to simplification and reduction of computational volume. The main idea of SuperPixels is to reduce the number of samples required for image processing. Each superpixel represents a homogeneous and meaningful region consisting of adjacent pixel sets that can be accessed and processed as a single data unit. By using superpixels, in addition to reducing the complexity of the space and increasing the processing speed, the quality of the results increases.

The superiority of CNN performance over other methods in which image features are extracted separately has led to extensive studies and the introduction of several efficient CNN models. In recent years, a successful CNN model called EfficientNet has been introduced by the Google research team (Tan & Le, 2019). In EfficientNet, the integrated compound scaling method is used to improve performance. In this method, the size of the network input images, network depth, and network width are scaled as a compound. This is because if only one of these three dimensions is scaled, the accuracy will only improve by about 80% (Heidary-Sharifabad et al., 2021c). The performance of the EfficientNet models has been evaluated and validated on the popular ImageNet dataset commonly used in learning transfer. The EfficientNet model is trained 5-11 times faster than previous CNN famous models, while the size of this model is up to 6.8 times smaller than them (Tan & Le, 2019). EfficientNet models are categorized as B0 to B7 according to their input image resolution and performance accuracy. In this study, we used EfficientNetB5.

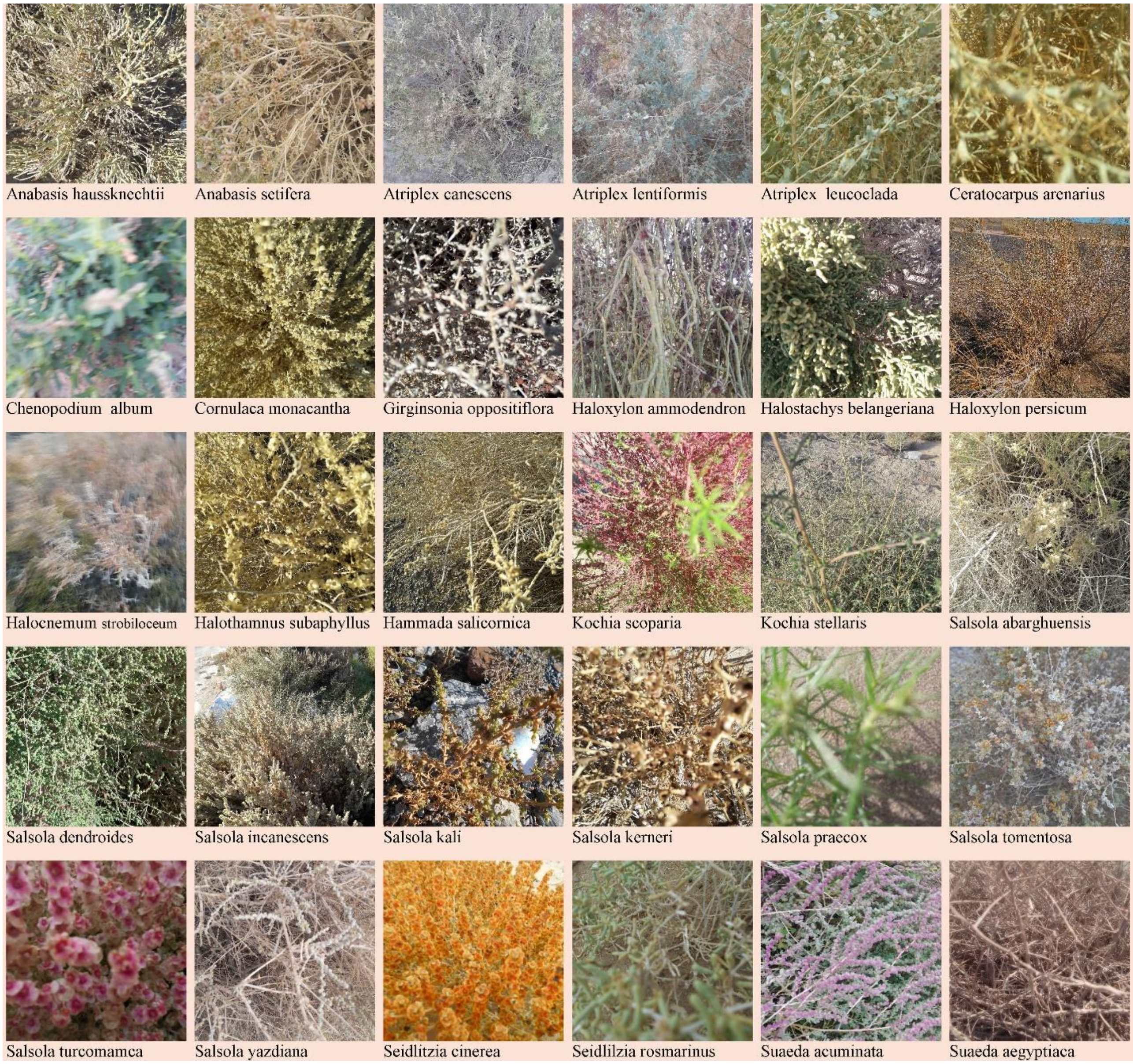

Fig. 2 - A sample image of each of the 30 species in the ACHENY dataset.

3. Results and discussion

The performance of the classification models was evaluated on the test dataset after training of models. The accuracy, precision, recall, and f1-score criteria for measuring the quality of the classification results were evaluated. The performance evaluation results of both models for all 30 classes are listed in Table 1.

The EfficientNet B1 model is based on the original ACHENY dataset (with 224×224 images). The superpixel method is then applied to the ACHENY dataset to create 448×448 images. These images are used in the proposed EfficientNet B5 model. Both of these models are applied to 2713 test datasets and are evaluated and compared by evaluation parameters. The results of the experiments indicate a superiority of about 3% accuracy of the proposed method and all evaluation parameters of the research have increased to a reasonable extent. This research is consistent with other projects such as (Qanbari & Jamali, 2015; He et al., 2021; Jamali et al., 2021; Jamali et al., 2022).

Table 1 - Results of performance evaluation of the proposed models on the test dataset.

Class	support	EfficientNet B1			EfficientNet B5		
		Precision	recall	f1-score	Precision	recall	f1-score
AnaHau	77	0.89	0.99	0.94	0.96	0.96	0.96
AnaSet	129	0.97	0.88	0.92	0.98	0.94	0.96
AtrCan	73	0.95	0.97	0.96	0.88	0.96	0.92
AtrLen	134	0.93	0.99	0.96	0.88	0.99	0.93
AtrLeu	63	0.88	0.95	0.92	0.92	0.94	0.93
CerAre	81	1.00	0.99	0.99	0.96	1.00	0.98
CheAlb	66	1.00	1.00	1.00	1.00	0.94	0.97
CorMon	110	1.00	0.78	0.88	0.98	0.95	0.96
GirOpp	31	1.00	0.90	0.95	0.91	0.97	0.94
HalAmm	93	0.91	0.85	0.88	1.00	0.85	0.92
HalBel	63	0.95	0.95	0.95	0.86	1.00	0.93
HalPer	116	0.59	1.00	0.74	0.90	0.97	0.94
HalStr	85	0.97	1.00	0.98	0.99	0.99	0.99
HalSub	97	0.98	0.85	0.91	0.98	0.93	0.95
HamSal	120	0.94	0.88	0.91	1.00	0.98	0.99
KocSco	91	0.87	0.99	0.93	0.86	0.97	0.91
KocSte	86	0.98	0.94	0.96	0.92	1.00	0.96
SalAba	74	0.71	0.89	0.79	0.81	0.78	0.79
SalDen	147	0.92	0.82	0.87	0.98	0.78	0.87
SalInc	116	0.90	0.97	0.93	0.97	0.99	0.98
SalKal	30	0.93	0.90	0.92	0.91	1.00	0.95
SalKer	91	0.95	0.65	0.77	0.90	0.93	0.92
SalPra	93	1.00	0.99	0.99	1.00	1.00	1.00
SalTom	97	0.96	0.98	0.97	0.90	0.98	0.94
SalTur	98	0.97	0.92	0.94	0.97	0.88	0.92
SalYaz	105	0.98	0.99	0.99	0.98	0.97	0.98
SeiCin	55	1.00	0.89	0.94	0.81	0.80	0.81
SeiRos	100	0.85	0.89	0.87	0.90	0.97	0.93
SuaAcu	118	0.98	0.84	0.90	0.97	0.94	0.95
SuaAeg	74	0.92	0.80	0.86	0.90	0.77	0.83
macro avg	2713	0.93	0.91	0.92	0.93	0.94	0.93
weighted avg	2713	0.93	0.91	0.91	0.94	0.94	0.94
Total accuracy			0.91			0.94	

Figure 2 shows the radar diagram related to the accuracy of the classification performance of the proposed models for each class in the ACHENY test dataset.

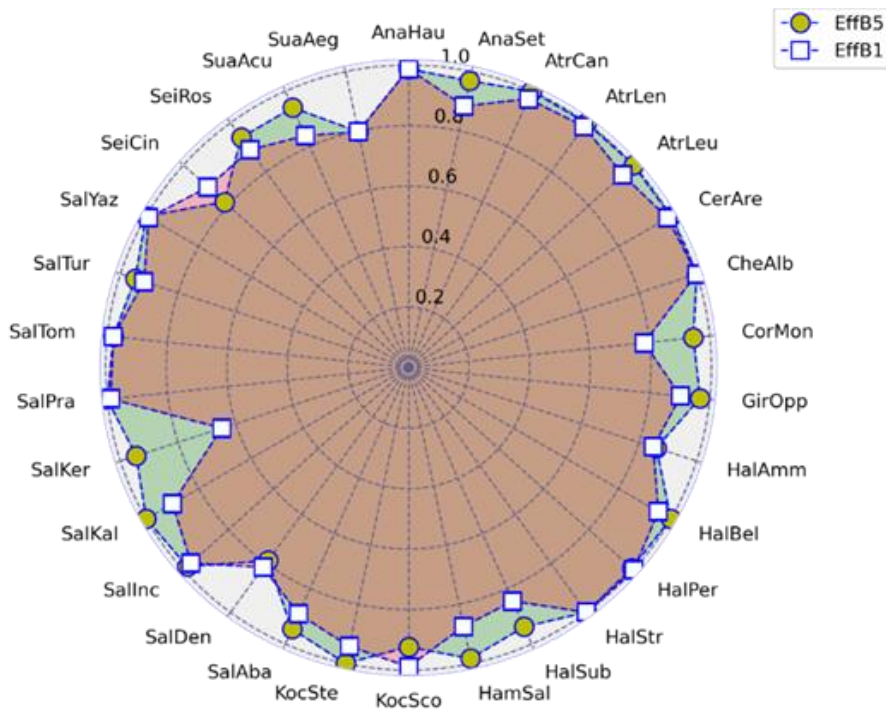

Fig. 2 - Accuracy of the classification performance of both proposed models for the ACHENY test dataset.

4. Conclusion

The importance of soil as a bed of life is not hidden from anyone. Soil provides food security, is a storehouse of carbon, protects water resources, reduces water pollutants, and also affects the global climate. Soil is the basis of the survival of living things and human activities, so preventing soil erosion is an important concern of humanity. Soil erosion involves the transfer of soil by factors such as water and wind, which leads to the loss of soil and water and nutrients in the soil. The successful mitigation of soil erosion is only possible through a combination of socio-economic, political, and scientific considerations (Morgan, 2009). To reduce soil erosion in hazardous areas, vegetation protection is one of the important considerations. Vegetation identification in these areas is very important and a prerequisite for their protection.

Computer vision enables it to analyze and process its surroundings, so using it, tasks that require human supervision can be performed automatically. In recent years, as a result of technological advances, it has become possible to develop artificial neural networks. This has led to the introduction of deep learning and its use in computer vision. The application of deep learning has increased the efficiency and accuracy of computer vision and expanded the range of its applications.

By destroying vegetation in desert and semi-desert areas, conditions are created that intensify soil erosion in these areas. Most of these areas are covered with some species of *Chenopodiaceae*. The effectiveness of *Chenopodiaceae* species in reducing soil erosion varies according to their characteristics and habitat. Therefore, the identification and protection of some species of *Chenopodiaceae* are very important in preventing soil erosion in some desert and semi-desert areas.

In this study, an efficient deep learning model for identifying *Chenopodiaceae* plants was introduced and evaluated. Using the SuperPixel method, we were able to create larger images from existing images. Using these images allowed us to use a larger deep learning model, resulting in improved classification accuracy. In future studies, more complete datasets of other important plant species can be collected and used on appropriate deep learning models. Deep learning can facilitate the identification and protection of vegetation to reduce soil erosion.

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Code availability (https://code.earthengine.google.com/e59371e901fb4316bf2b571d1be1d5c0)

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