ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

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WEED DETECTION AND CLASSIFICATION USING DEEP LEARNING

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

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ABSTRACT

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CNN can solve miscellaneous complications in several applications suchlike manufactures, robotization, sustainable environment, and medical processes. Except for these areas, precision agriculture according to plant crop management is another essential domain. It must detect and restrain weeds in their early growth stages to accomplish plant crop management. Non-chemical weeds control is a crucial aspect of sustainable organic agriculture. This thesis explores the state-of-the-art deep learning algorithm and proposed a novel and simple convolutional network for weeds detection referred to as CovWNET to detect and classify crop and weeds species. Along with this, transfer learning is implemented with conventional benchmark models in order to compare their performance with the proposed model. CovWNET has the second smallest size among the implementations compared in this study. It has roughly 1.5 times more parameters; however, it achieves 2.8% more accuracy as compared to the smallest network, MobileNetV2. Correspondingly, CovWNET has approximately seven times lesser number of parameters, and 1.7% less accuracy compared to the most accurate model of DenseNET. Performance metrics of precision, recall, F1-score, and support, are employed to evaluate the overall performance of each class of the dataset.

Keywords: Deep leaning algorithm, Convolutional neural network, CovWNET, Transfer learning architecture, Weed's classification and detection.

ÖZ

YÜKSEK LİSANS TEZİ

DERİN ÖĞRENMEYLE ZARARLI OTLARIN TESPİTİ VE SINIFLANDIRMASI

MD. NAJMUL MOWLA

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
ELEKTRİK ELEKTRONİK MÜHENDİSLİĞİ ANABİLİM DALI

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CNN, imalatlar, robotizasyon, sürdürülebilir çevre ve tıbbi süreçler gibi çeşitli uygulamalarda çeşitli komplikasyonları çözebilir. CNN yönteminin kullanılabileceği bir diğer önemli alanda hassas tarım uygulamalarındır. Bitki mahsul yönetimini gerçekleştirmek için önemli bir adımı yabani otları erken büyüme aşamalarında tespit edilmesi ve kısıtlanmasıdır. Kimyasal olmayan yabani ot kontrolü, sürdürülebilir organik tarımın çok önemli bir yönüdür. Sonuç olarak, bu tez, en gelişmiş derin öğrenme algoritmasını araştırdı ve mahsul ve yabani ot türlerini tespit etmek ve sınıflandırmak için CovWNET olarak adlandırılan yabani ot tespiti için yeni ve basit bir evrişimsel ağ önermektedir. Bu tezde aynı zamanda birlikte, transfer öğrenme uygulamaları da kullanılmış ve bu uygulamalar ile önerilen modeller kıyaslanmıştır. CovWNET, bu çalışmada karşılaştırılan uygulamalar arasında en küçük ikinci ağ modeli olmuştur. Karşılaştırma yapılan transfer modeli ağları arasında en küçük ağ olan MobileNetV2'e kıyasla kabaca 1,5 kat daha fazla parametreye sahiptir fakat %2.8 daha fazla test doğruluğuna erişmiştir. Ayrıca en yüksek doğruluk skoruna sahip olan DenseNET modeline kıyasla %1.7 daha az doğruluk hassasiyetine sahiptir fakat DenseNET modellinden yaklaşık yedi kat daha düşük parametrelere sahiptir. Performans metrikleri olarak kesinlik, geri çağırma, F1 puanı ve destek parametreleri veri kümesinin her sınıfının genel performansını değerlendirmek için kullanılmıştır.

Anahtar kelimeler: Derin Öğrenme Algoritmaları, Evrişimsel Sinir Ağları, CovWNET, Transfer Öğrenme Mimarisi, Zararlı Ot Tespiti ve Sınıflandırılması

EXTENDED ABSTRACT

Agriculture's expansion is an absolute necessity for avoiding extreme poverty and increasing wealth by 2050, with resources being delivered to almost 9.7 billion people. It is directly responsible for more than 25% of global GDP growth in most developing nations (Agriculture Overview n.d.). Alternatively, agricultural outturns serve the community with essential requirements to sustain their livelihood. Therefore, it is necessary to extend agriculture production keep pace with the quantity of the global population in order to preserve the food demand. As a result, it is apparent that agriculture production must be increased to keep up with the world population in order to meet food demand. Farmers should practice proper agricultural crop management and recognize weeds in their initial stages. The primary goal is to identify and classify weeds that are eventually harmful to crops and agricultural yields.

Visual inspection is the initial pattern used by experts to detect and categorize weeds; however, this method requires knowledge and might lead to an incorrect diagnosis. On the other side, they often provide chemical herbicides in order to prevent the weeds, which are costly and detrimental to the field's soil. As a result, another low-cost innovative approach is required to ensure that weed categorization and detection can be done with confidence, even in the absence of an expert.

In this research, Convolutional neural networks (CNNs), a deep learning approach (DL), were utilized to recognize and categorize the weeds automatically. DL is an artificial intelligence (AI) framework for locating functions that allow a computer to work without being directly directed by a human. Whereas CNN is a DL method that is frequently used in computer vision. CNN performs functions including detection, identification, and classification on the images. In addition, an open-access plant seedling weeds dataset has been estimated regarding 12 varieties at various majority stages. The classification was done by a proposed CNN architecture and transfer learning architecture. The architectures used for transfer learning were DenseNet201, MobileNetV2, VGG16, VGG19, and Xception. Several input shapes are employed for the training of transfer learning architectures. The proposed CNN model consists of a sequential convolutional layer, a pooling layer, and a fully connected layer, with the dropout layer serving as regularization and ReLU as the activation function.

A proposed CNN architecture and transfer learning architecture that is DenseNET201, MobileNetV2, VGG16, VGG19, and Xception were applied to detect and classify the weeds. Several input shapes are employed for the training of transfer learning architectures.

According to the complete study, the overall height accuracy was obtained by the DenseNet201 model is 93% with 18,321,984 parameters. On the other hand, the proposed model achieved the second heights prediction result of 91.3%, with 3,348,702 parameters which are 1.5 times more parameters than MobileNetV2, yet it achieves 2.8% higher accuracy.

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ABBREVIATIONS

1D	: One Dimension
2D	: Two Dimension
ADAM	: Adaptive Moment Optimization
AI	: Artificial Intelligence
ANN	: Artificial Neural Network
API	: Programming Interfaces
CNN	: Convolutional Neural Network
CovWNET	: Convolutional Neural Network for weeds detection
DenseNet	: Dense Convolutional Network
DL	: Deep Learning
GDP	: Gross Domestic Product
GPU	: Graphics Per Unit
IoT	: Internet of Things
KNN	: K-nearest neighbors
ML	: Machine Learning
NB	: Naive Bayes
ReLU	: Rectified Linear Unit
RF	: Random Forest
RGB	: Red Green Blue
RMSprop	: Root Means Squire Propagation
SA	: Smart Agriculture
SGD	: Stochastic Gradient Algorithm
SVM	: Support Vector Machine
TPUS	: Tensor Processing Unit
UAV	: Unnamed Ariel Vehicles
VGGNet	: Visual Geometry Group

YOLOV3 : You Only Look Once

1. INTRODUCTION

1.1. Weeds and Its Impact on Agriculture

Agriculture can be conceptualized as the superintendence of worldly ecosystems to turn their productive potential to serve human necessities. Alongside, agriculture contributes to humankind, i.e., "ecosystem co-operations", mainly in initial products such as foodstuffs, supplies, timberlands, textures and additional fundamental products. The recent investigation reveals a significant conflict among the rising demands of agriculture and the preservation of services other than initial production.

The persistence of organic miscellaneousness in the functioning of the agricultural ecosystem has been disputed for many decades. However, it is hardly new that the perception of the operative association has promoted investigation on the correlation within natural diversity, including its performance in ecosystems. Moreover, insufficient knowledge on the utilitarian estimation of plants in the agricultural ecosystem includes a comparatively inadequate argument for natural diversity preservation in farmed panoramas. Therefore, deficiency of experience somewhat appears because several investigations conducted in agricultural ecosystems have concentrated on estimating the significance of plants rather than on their function in processes. Nevertheless, the gap within the two strategies requires to be spanned as it is the consequence of agricultural practices on functional diversity, and hence the requirement of services is of interest for promoting sustainable agriculture.

In general, plant crops have hampered diverse aspects of unpredictable weather conditions, soil and moisture, shortening of water, and weeds. Weeds are unwanted plants that eventually harm agricultural yields and severely intimidate entire production and biodiversity. It decreases land and forest fertility, replaces indigenous species and significantly contributes to land and water degeneration. Besides that, it exhibits yield damage and increases farmers 'cultivation expenses more than other natural impacts such as bugs, harvest pathogens, root-feeding nematodes, and warm-blooded pests. Usually, Weeds can damage crop yields as well as inflation expenses of annual production. It dragging crops water and necessary nutrients; as a result, the preferable yield of crops has become drained more than about 45%-95% (Berge, Aastveit, and Fykse 2008). Besides that, it discharged natural elements that restrain yield growth, treating pests and diseases by restraining air transmission throughout the crop and hindering with or poisoning crop harvesting. Weeds possess a more significant biogenetic heterogeneity as compared to crops. Contrariwise, it manifests a diversity of characteristics by the variance of the natural resource: sunlight, water, soil nutrients and humidity and carbon dioxide (CO2). In effect, weeds revealed exceeding unusual growth and generative response. It can be disputed that several weed varieties produce the C4 photosynthetic pathway that is indirectly responsible for producing CO2 corresponding to C3 crops (Karaca and Dursun 2020) , (Ziska n.d.).

1.1. Smart Agriculture: Weeds detection

Smart agriculture (SA) is an emerging concept that indicates operating yields by employing technologies, i.e., and AI, the internet of things (IoT), automation, and unmanned aerial vehicle (UAVs), to enhance the capacity and feature of commodities while optimizing the individual activity demanded by production. SA comprise the identification of modifications inside cultivation. The intention of more precision of agricultural system, SA required sensors and application technology that can detect deviations and change the depth of an application. For this purpose, several procedures can be identified as online schemes, adopting the sensor analyses directly to differ the application, and offline schemes, wherever the position information is already available for the entire domain before application.

SA contributes to various applications such as water saving, soil moisture and nutrition, weather forecasting, herbicide and pesticides. The variation of these domains is forming a significant impact on weeds production that are mentioned earlier. By employing the SA domain, it is possible to collect the variation of environmental data by deploying the required hardware. Alongside UAVs and robots with AI framework in SA applications allow the potential to observe agricultural fields on a per-plant basis, which can lessen the volume of herbicides and pesticides that must be implemented. Essential information for the farmer and self-governing agriculture robots is the knowledge about the variety and arrangement of the weeds on the field, and UAVs are an exceptional platform to approach this challenge. Recently, UAVs introduced significant advancements to identify weed's early post-emergence stage from both earth and aerial terraces within the computer-aided processing of data (Singh et al. 2020). UAVs are becoming an overwhelming retrieval system for weed identification and management since they can acquire images of the entire agricultural field with a large spatial resolution and low cost. Nevertheless, despite significant progress in UAV procurement systems, the automatic apprehension of weeds persists as a challenging problem since a remarkable resemblance to the crops. As a result, deep learning and convolutional neuronal networks (CNNs) are commonly used in UAV images for sustainable weeds detection (Bah, Hafiane, and Canals 2018). Autonomous UAVs allow probability in SA applications by monitoring agricultural farms on a per-plant basis, as they possess the skill of procuring high-resolution representation, presenting comprehensive information for the allocation of crops and weeds in the field. In this concern, UAVs offer a cost-efficient solution for providing high-quality outline aptitudes.

Weeds are reducing by using herbicides & pesticides; however, the massive use of herbicides & pesticides are harmful to crops and those occurring agronomic and environmental obstacles. Therefore, a certain volume of herbicides should be established that are appropriately suited for the agricultural field. As well Efficient agrochemical sprayers practicing intelligent control methods can considerably minimize the chemical input, weed control expense, and unfavorable environmental contamination. In contemporary, most UAV sprayers are designed to manage aerial broadcast applications and apply them to the autonomous convention. However, remote sensing for weed detection and real-time weed classification applying CNN and machine learning (ML) has enhanced the ability to execute site-specific weed management strategies. UAV sprayers have capable of developing the effectiveness of applications when respectively operating earlier mapped weed patches.

1.2. Problem Description and Proposed Method

Weeds control is indispensable to agriculture since it is incredibly harmful for agriculture production. Some of the early-maturing weed control schemes are still existed included smothering, burning, and crop rotation. Another procedure is carrying bugs that attack only the undesired plant and damage it while leaving the crop plants uninjured. However, these methods are necessary; additionally, centers are conceivably more standard nowadays, especially herbicide compounds. Preventing weeds by chemical-based herbicide results provokes climate ascendance and soil and earth water pollution (Dai et al. 2019). Eventually, the organic production of plants and crops demands non-chemical weed control. In other words, the traditional way of hand weeding is even the initial accessory for controlling the weeds that demand human interface as well as labor expense. As a result, farmers have to summate a considerable expenditure for each annual production. In addition to, labor cost is going to increase day by day substantially. Therefore, a visual approach to categorizing plant crops and weeds is essential for ecologically sustainable weed management.

Weeds plant crop detection is a state-of-the-art challenging exploration in this modern period (Hasan et al. 2021). In fact, when farmers cultivate a crop in the field where its soil property and pre-available micro seeds are additionally liable for the growth of weeds. Therefore, the case of accurately classifying, identifying, and detecting weeds is a big issue. As a result, traditional agriculture has taken the shape of intelligent agriculture with the help of computational learning to discover the padding growth of weed along with diverse crops and plants.

Moreover, experts mainly count on visual inspection to diagnose plant diseases that require experience and may lead to the wrong diagnosis. Therefore, using another inexpensive diagnostic method is essential to allow the diagnosis to be made with confidence, even in the absence of an expert.

Deep Learning (DL) is a subcategory of machine learning that permits machines to learn from data affiliated with algorithms extracted by the function of the intellect called artificial neural networks (Abdar et al. 2021). In recent years, miscellaneous research studies have become stand on it to manipulate a specific problem. It can be represented as the progression of analyzing an image to classify it to a specific class. Moreover, image classification can be brought to bear in various applications, such as face and text recognition (Lu et al. 2021), self-driving vehicles (Grigorescu et al. 2020), and agricultural applications (Bera and Shrivastava 2019).

A Convolutional Neural Network (CNN) is an algorithm of DL methods that can be considered a factual appliance for image classification (Wang et al. 2021). It can prefer images as input, recommend bright objects in the image, and separate them from one to the other. It included several convolutional, pooling, and fully connected layers.

Transfer learning is a machine learning algorithm that implies the applied model that has been trained for a specific task as long as to process another related task (Zhuang et al. 2021). It developed with several architectural models: DenseNet201 (WangShui-Hua and ZhangYu-Dong 2020), MobileNetV2 (Sandler et al. 2018), VGG16 (Qassim, Verma, and Feinzimer 2018), VGG19 (Noon et al. 2020), and Xception (Dhillon and Verma 2019) .

A novel CNN architecture convolutional network for weed detection (CovWNET) has been applied in this research. For this purpose, an open-source image dataset, 'plant seedlings dataset, 'consists of 5,539 images separated into twelve classes (Giselsson et al. 2017). The applied dataset was prepared by the collaboration between Aarhus University and the University of Southern Denmark. Besides that, the learning rate, which can be considered the essential hyperparameter in training of CNNs, is also discussed in this study. The hyperparameter helps control the flow of learning of the CNN model until it appears at the minimal values of error. Moreover, it is considered one of the integral variables that support acquiring the better efficiency of the model.

1.3. The framework of Thesis

The rest of this thesis is organized as follows - Section 2 discusses the related works and literature review. Section 3 presents the general structure of deep learning and machine learning, convolutional neural networks and various layers of convolutional neural networks. Section 4 consists of the description of an applied dataset for weeds classification and detection. Section 5 describes the evolution of results and discussion. Finally, Section 6 gives the conclusions for the research work.

2. RELATED WORK

The advancement of research and development, together with automation and AI, are adequately utilized for the welfare of agriculture. As a result, ML and DL methods typically have been walked on weed classification, detection, segmentation, recognition, and eventually weed management. In recent, DL application is dependably used to the progression of weeds management in terms of its outstanding performance than traditional image processing techniques (Kamilaris and Prenafeta-Boldú 2018).

Moreover, the existing research has been carried on orderly surroundings with appropriate lighting, species, and environment. Therefore, it has been a significant challenge to classify weed species for selective targeting in crop situations accurately. Kun Hu et. El. proposed Graph Weeds Net (GWN) graph-based deep learning architecture. It has recognized numerous classes of weeds from conventional RGB images collected from yields. The framework was evaluated in a benchmark dataset that achieving cutting-edge execution with the maximal accuracy of 98.1% (Hu et al. 2020). Besides that, Lohitha et al. offered another DL method to detect weeds in the agriculture fields. They used the CNNs to extract features and use InceptionV3 and U_Net for classification, respectively, and achieved 90% accuracy (Boyina et al. 2021).

On the other hand, weeds have existed with diverse categories of plant species. As a result, identification of weeds in vegetable cultivation is more challenging than crop weed identification. Xiaojun et al. proposed CenterNet for the ground-based weed identification in the yield of vegetables. For this purpose, a trained CenterNet model was applied to bound boxes to trace the vegetables, and exerted bounding boxes had been considered weeds. In this way proposed architecture obtained accuracy 95.6%, 95.0%, 0.953, respectively, for precision, recall, and F1 scores. Besides that, the research index achieved a high segmentation quality, i.e., $19R + 24G - 2B \geq 862$, which is a measurable cost compared to the wildly used ExG index (Jin, Che, and Chen 2021). M. Dian Bah et al. designed a CNNs based classification system to identify weeds in green vegetables: spinach, beet, and bean. For this purpose, they consolidate DL with line detection to execute the classification scheme. The results showed that weeds detection was effective in different crop fields, such as precision score achieved the highest accuracy for spinach and bean is 93%, 81% and 69% (Bah et al. 2018).

To develop an efficient weed management system, it is necessary to define the particular location and determining the factual information about weed species. Anais et al. designed pre-trained VGG16, ResNet50, and InceptionV3 models for image classification. On the other hand, the You Only Look Once (YOLOv3) library has been proposed as an object detection model trained to locate and identify different weed species within an image. The proposed method achieved the best performance by VGG16 where an accuracy of 98.90% and an F1 score of 99%. Whereas, YOLOv3 model helped to locate and identify multiple weeds within an image with average precision scores of 43.28%, 26.30%, 89.89%, and 57.80%, respectively (Ahmad et al. 2021). In order to accurately specify the classes of weeds, Dmitrii et al. presented transfer learning methods for Dense Convolutional Neural networks among 18 several weed species. In addition to transfer, learning helps identify the leaf characteristics directly obtained from the input data representation with 71.81% top1 accuracy and 93.45% top3 accuracy (Vypirailenko et al. 2021).

Productive agricultural yields can be presented by preventing the weeds in their early growth stage. It can be beneficial for the cultivation of soil as well as crops health. Trupti et al. designed a hybrid AgroAVNET architecture by the combination of AlexNET and VGGNET. The result findings using AgroAVNET are about 99%, and it showed that AgroAVNET is more reliable and convenient than AlexNet and

VGGNET with less training time to learn new features (Chavan and Nandedkar 2018). In addition, Sanjay et al. also proposed a Mask Regional Convolutional Neural Network model to detect cranesbill seedlings during their early growth stage. The proposed model has achieved 100% and 98% accuracy of the training and validation phase (Patidar et al. 2020). Moreover, accurate classification helps to acquire the topmost efficient model for the detection and identification of weeds. Therefore, several researchers contributed their research by establishing their own customize architecture in terms of the deep learning algorithm. Carlos et al. proposed three pre-trained models and represented a comparison between İnceptionV3, VGG16, and Xception. It has been shown that Xception achieved 86.21% accuracy (Mamani Diaz, Medina Castaneda, and Mugruza Vassallo 2019). In addition, Martinson et al. proposed deep convolutional neural networks for weeds classification. They applied five pre-trained architectures, VGG16, inceptionV3, DenseNet121, Xception, ResNet152V2, and illustrated comparisons according to their accuracy. This proposed model represented accuracy 0.713, 0.779, 0.750, 0.790, and 0.780, respectively, which has been considered the top1 accuracy of the model (Ofori and El-Gayar 2020).

Alternately, researchers are additionally concentrating on how to utilize the targeted amount of herbicides for the weeds. Several works have been done for accurate and sustainable herbicide sparing. For example, Shahbaz et al. proposed a method that was performed and assessed relating high-resolution UAV imagery taken across two separate target fields. This model achieved an accuracy of 95.3%, whereas the overall average accuracy was 94.73% (Khan, Tufail, Khan, Khan, and Anwar 2021). Jizhan et al. developed another DL method for a strawberry field, classifying weeds by CNN and precisely spray on aspired weeds ends. For DCNNs models, they used AlexNet, VGG-16, and GoogleNet architecture and twelve thousand four hundred forty-three images. It can be shown that the VGG-16 pattern achieved more leading values, and a sprayer with the VGG-16 architecture can deliver special performance that offers it more ideal for a real-time spraying application (Liu, Abbas, and Noor 2021). Shahbaz et al. proposed UAV-based two-step target recognition system sprayers that are spayed actual real-time perception systems of spraying areas. This DL model attained an average F1 score of 0.955, while the classifier identifying medium estimate time was 3.68 ms. They also mentioned that their model could be expanded in real-time to UAV-based sprayers for precise spraying (Khan, Tufail, Khan, Khan, Iqbal, et al. 2021). Jialin et al. proposed another accurate DCNN model for weeds detection where VGGNet obtained 95% accuracy in F1 score. Besides that, they also included detectNet for detecting weeds, where it achieved F1 scores of 99% accuracy (Yu et al. 2019).

Minimal amount of research focused on conventional machine learning techniques for weed detection (Mennan et al. 2020) . Nahina et al. proposed ML-based weed and crop classification by random forest (RF), support vector machine (SVM) and k-nearest neighbours (KNN), which are examined to detect weeds using UAV images. The experiment results showed that RF achieved a height of 96% accuracy, whereas SVM was 94% and KNN 63% (Islam et al. 2021). Several numbers of researchers have been considered SVM for weeds detection. For example, Ahmed et al. classified six types of weeds species by applying the SVM model. In addition, the model allowed for achieving an accuracy of about 97% with any misclassification (Ahmed et al. 2012). Adel et. El. proposed another model employed with the shape features associated with SVM and artificial neural network (ANN). The finding of this model was 92.92 % for ANN whereas 95% for SVM (Bakhshipour and Jafari 2018).

3. GENERAL ARCHITECTURE

Agriculture is taking a significant place from the very ancient period of civilization; whereas, due to the lack of proper planning and management, uncertainty of weather condition and environmental effect many country people cannot take proper advantage of it. Thus, farmers face frequent annual losses, and the amount of gross production corresponding equal to the world population is getting reduced day by day. Besides that, the lack of knowledge on utilizing the advanced technology and inaccessibility of a simple framework for the particular agriculture application can be suspected as the major issues in food scarcity.

In addition, AI technologies that boosting yield by detecting weeds, controlling pests, monitor soil and generating the real-time data that can assist to compose a fitting crop management (Jha et al. 2019). AI practice algorithms to enrich the arithmetical solutions that can be repeated the analytical, carnal, and evolutionary action of realism and human beings. It can perform with random cognition that does not demand any particular domain. Besides that, it can be served basis on previous learning. ML and DL are the architecture of AI that promotes device operation and assists in gathering further elevate technology.

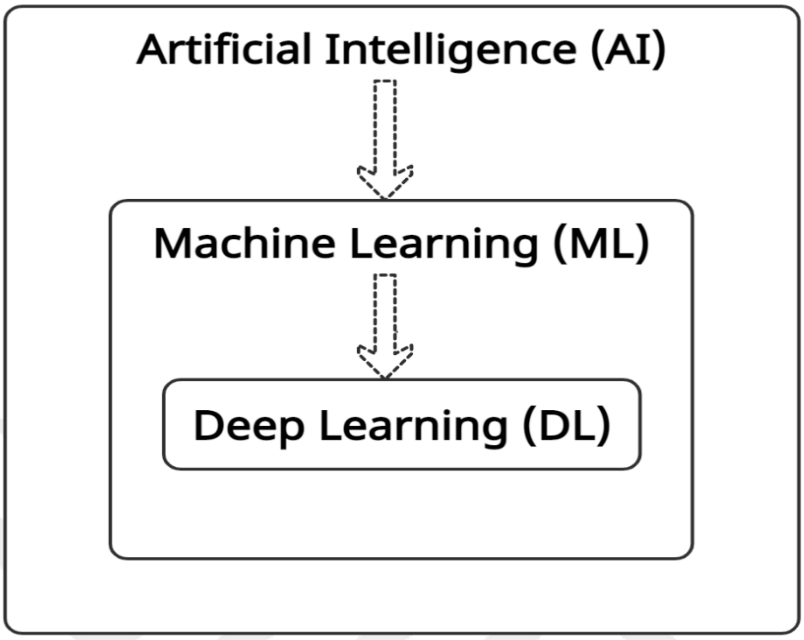


Figure 3.1. Illustration of AI with the particular branch of ML and DL

3.1. Machine Learning (ML)

ML is a subset of artificial intelligence that prepares to execute a particular task bestowed training data (X.-D. Zhang 2020). ML algorithm neither developed with comprehensive with program nor able to complete the entire task. X set of samples for an ML can be express as following

$$X = \{(a_i, b_i)\}$$

Where, $a_i \in R$ represents that a_i is the set of R and denotes observed features characterizing the i-th sample's properties, and b_i is the related output.

ML architecture is progressed in this cutting edge with a revolutionary refinement that prepares over the expertise extent with ANN, SVM, RF, Naive Bayes (NB), and KNN. Its framework is precisely basis on computational expression, where the key objective is forming observations and predictions with the help of computational devices.

ML algorithms are often categorized as supervised, unsupervised, and reinforcement learning. Supervised learning is the most used algorithm which utilizes labelled training data to produce architectures that can process previously imperceptible data. On the other hand, unsupervised learning is driven by the data to assemble, classify and incorporate data according to its features in a way that enables humans to understand it. Alternatively, in reinforcement learning, the machine comprehends establishing a design within an inconstant and complicated environment. It diverges from supervised ML, where it does not demand labelled input and output data. Categories of ML is illustrated in Figure 2.

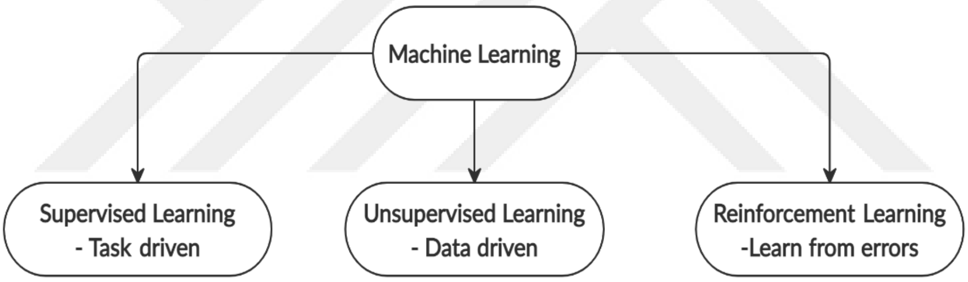


Figure 3.2. Categories of machine learning algorithm

3.2. Deep Learning

Deep Learning is an emerging approach that has been comprehensively applied in computer vision, transfer learning, natural language processing, and semantic parsing. İt has become prevailing on account of its accessibility of graphics per unit (GPU), progressing state-of-of-art of the machine learning algorithm, maximum accuracy can be effortlessly achieved by employing ImageNet Large Scale Visual Recognition, and most affordable of its computing hardware (Guo et al. 2016). Nevertheless, deep learning arises not only with the advancement of processors but also with the appearance of vast amounts of data. It delegates ML algorithms that conduct a large scale of enormous layers to process it. In addition, deep learning deals with the layered multiplex structure of neural networks that can accomplish multitudinous function classification, regression, and segmentation.

3.3. Convolutional Neural Network

Additionally, CNN is generated from a deep learning architecture usually utilized to identify, classify, and visualize the image data (Gu et al. 2018). Notwithstanding, it can be possible to achieve image classification and identification by using neural networks; nevertheless, it becomes a steady and time-consuming process, since images are formatted with multiple pixels. As a result, CNN extracts the features from images, can solve this problem using its layers. CNN is constructed with several sorts of layers shown in Figure. 3.

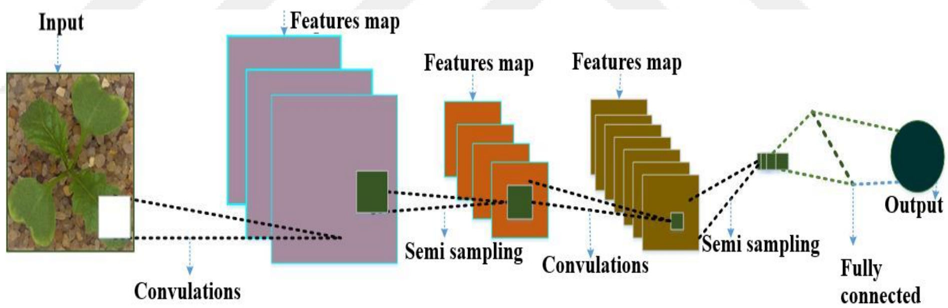


Figure 3.3. A complete diagram of CNN architectures

3.3.1. Input and output layers

The input layer follows the image data extracted from the dataset. Moreover, this image data consists of red, green, and blue, i.e., RGB is considered a three-dimensional matrix. The convolutional layer categorizes the basis layer for the CNN model. This layer extracts the features of the image by using filters. These features may or may not be perceivable by humans. The inputs and outputs of the CNN networks are recast from their initial specifications in order to fit them to the diversity of image dimension and quantities of plant species. Thus, except for the input image size, all of the network's input and output specifications are identical. Even though convolution operation is the same as translation, it is not the same as scaling or rotation.

3.3.2. Convolutional layers

Convolutional layers eventually ease the proportion of images by conserving their essential features. In contrast, pooling layers are deployed to minimize the parameters and computation of the model. This operation detects each feature by applying distinct two-dimensional filter on the image. There can be several sets of kernels that are considered as learnable filters. The most common filter sizes are 3 by 3, 5 by 5, and 7 by 7. In fact, the number of channels in the input represents the number of filters. The first convolution layer input also demonstrates the depth of images with 1 and 3 which indicates the grayscale and RGB, respectively.

3.3.3. Rectified Linear Unit (ReLU)

The Rectified Linear Unit (ReLU) is generally the most preferred activation function in the deep learning algorithm. ReLU returns 0 if it the input is negative, whereas it returns the value of the input if it is positive. It performs by thresholding values at 0,

$$f(a) = max(0, a)$$

It can be demonstrated as the resultant outputs is 0 when $a < 0$, and in contrast, $a \geq 0$ when the resultant outputs is a linear function. ReLU function can perform more analytical as compared to the remaining nonlinear functions. The difference between nonlinear functions such as sigmoid, leaky ReLU, and Tanh with ReLU function are illustrated in Figure 4. ReLU function can regenerate the input by a turn back of applied data.

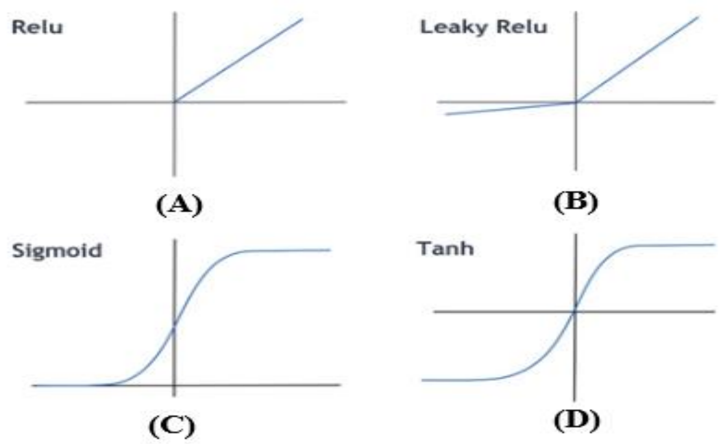


Figure 3.4. Correlation within activation function: (A) ReLU, (B) Leaky ReLU, (C) Sigmoid and (D) Tanh.

$$g(x) = max(0, x) \tag{3.1}$$

$$g(x) = max(\delta x, x)\, with \delta \ll 1 \tag{3.2}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3.3}$$

$$tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3.4}$$

3.3.4. Pooling layers

In general, pooling layers are liable for diminishing the extension of a feature that can help to lessen the number of parameters and computation. It operates by utilizing the two-dimensional filter slides over each feature map. Max Pooling is considered as the standard function that performs pooling operations. It discriminates against the maximal norm in each window that was eventually covered by the filters. The max pooling 2x2 process shows in Figure 5.

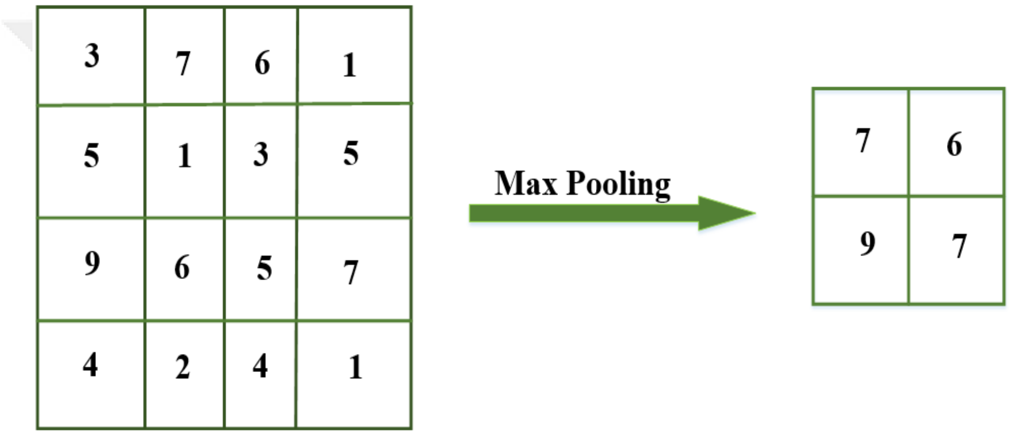


Figure 3.5. Max Pooling Process employing 2x2 Filters

3.3.5. Flatten Layers

The Flatten layer transforms a two-dimensional (2D) feature map from the resultant pooling operations to a one-dimensional (1D) feature vector. It is essential to assemble the fully connected layer that does not treat data with varied dimensions. Flattening of 2D feature map to 1D shown in Figure 6.

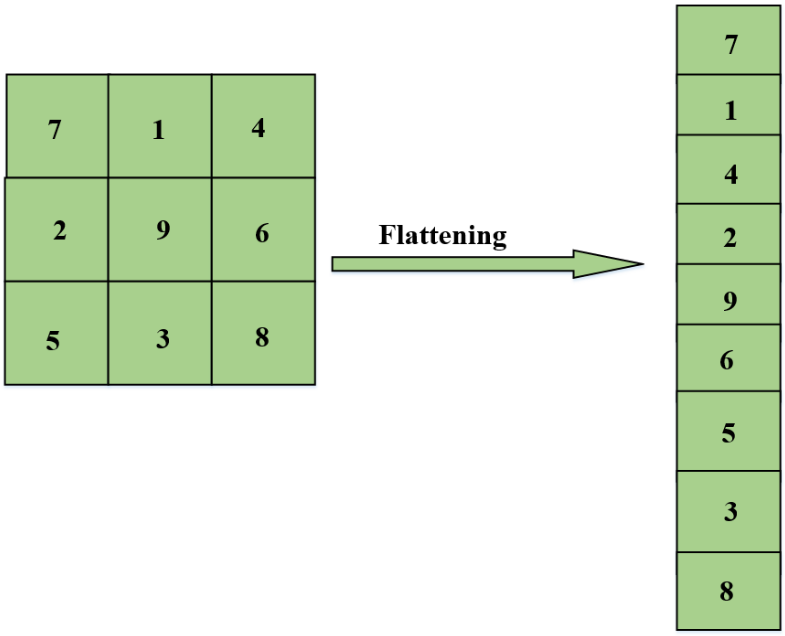


Figure 3.6. Flattening of 2D feature map to 1D

3.3.5. Fully Connected Layer

The resultant feature maps of the terminating convolution as well as pooling layer are usually flattened that interlinked to several fully connected layers, i.e., dense layers. In this layer, each and every input is interrelated with connected output individually with the help of learnable weight. After generating the polling layers by the corkscrewed of convolution and down sampling, a subset of fully connected layers manipulates the pooling layers in terms of the resultant output of the network. In addition, the upgraded fully connected layer possesses output nodes identically as the respective fully connected layer that obeyed by ReLU, as mentioned earlier.

3.3.6. Learning Rate

Learning rate is a hyper parameter that resolves the phase dimension as well as controls the speed of architecture learning. Besides that, it represents the amount of the updated weights during the optimization. It can be considered as long as peripheral essential hyper parameter perfection of tuning, and it has ranged between 10^-6 to ± 1. Nevertheless, a high learning rate sometimes accelerates the learning process; as a result, the running model would be getting errors and crashed automatically. On the other hand, a low learning rate can lead to a long training time and an incapable of running down error rate. Distinguished amplitude for the learning rate in a specific problem needs to be investigated by observing the prediction performance for different values. Therefore, in this research, various learning rate values are applied to modify the model accuracy. As a result, nonidentical accuracy has been found by fluctuating the learning rates.

3.3.7. Optimizer

Optimizer is a practical approach that permits achieving the best result since the optimizer is accountable for updating the weights to diminish the loss function. Several optimizers are applied in terms of the characteristic of image data. As a result, adaptive moment optimization (Adam) has been considered for this current research (Z. Zhang 2019). As a matter of fact, it is user-friendly, computationally efficient, and demands small memory to process, and it is usually applied for deep learning-based research. In general, adam optimizer is associated with reforming existing stochastic gradient algorithms (SGD) with momentum and root means square propagation (RMSprop).

Updated weights and biases are demonstrated as follows:

$$vdw = \beta \cdot vdw + (1 - \beta) \cdot dw \qquad 3.5$$

$$vdb = \beta \cdot vdb + (1 - \beta) \cdot db \qquad 3.6$$

$$W = W - \alpha \cdot vdw \qquad 3.7$$

$$b = b - \alpha \cdot vdb \qquad 3.8$$

3.3.8. Overfitting

Overfitting interrupts against obtaining high accuracy within test data. The other way it can be defined as the model has achieved high accuracy in the training data; however, it fails to predict the test data. As a result, it would become challenging to detect the object with the desired accuracy. Dropout, which belongs to regularization, is usually applied to minimize the overfitting into the model. It regulates the weights and abates the impact of these weights on the model. Additionally, dropout declines scattered neurons in neural network layers that surpass overfitting in the training process Thus, regularization is a usually applied process to eliminate overfitting. This approach can constrain the weights associated with the features that cause the overfitting, diminishing the influence of certain weights toward the architecture.

Dropout is a regularization technique that drops neurons in neural in a random way during the training. The advantage of practicing dropouts is that neither high weight values will be allowed to a neuron in the model, so the weight values will lose their excessive effectiveness that causes overfitting. This method prevents the output of the layers from depending on specific neurons.

3.4. Transfer Learning

Transfer learning is a process in deep learning algorithms that helps to recover issues rise due to insufficient training data (Zhuang et al. 2021). Additionally, the initial intention is to apply this method for regenerating comparable training data and the test data. This process would drive tremendously positive outcomes on altogether input and target domains that are literally complex to elevate since insufficient training data. Basically, transfer learning stands on several factors to refine the learning. Therefore, in the beginning, initial performance obtaining within the target domain by using transferred knowledge in advance of any further learning is done. Afterward, it holds a considerable duration to detect the target domain and assimilate to the volume of time to learn it from scratch. In the end, the utmost execution can be achieved in the target domain compared to the final level beyond transfer. On the other hand, a negative transfer can be produced to decrease the performance. In fact, it is a significant challenge to reveal transfer methods by producing positive transfer as similar that the negative transfer has refused. Transfer learning process illustrated in Figure 7. Fine-tuning convolution neural networks such as DensNet201, MobileNetV2, VGG16, VGG19, and Xception have been considered for this current research that show in Figure 8. The model weights are trained with the ImageNet approach and carry more than a million images classified into hundreds of labels.

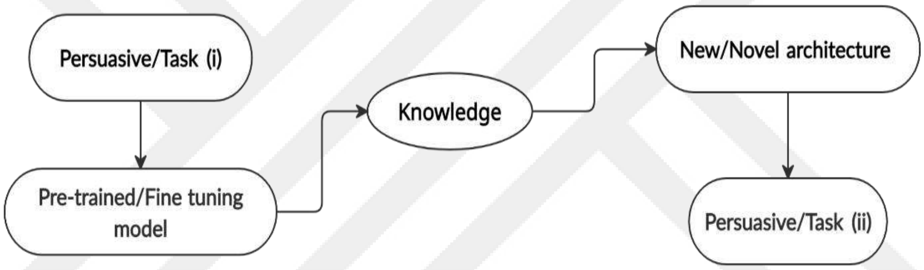


Figure 3.7. A simple diagram of Transfer Learning Method

3.4.1. DenseNet

DenseNet has been considered as advanced proposed CNN architecture, where each of the layers is connected to a dense block (WangShui-Hua and ZhangYu-Dong 2020). In this case, the layers can access feature maps through their anterior layers, which utilize the executive features. Besides that, this model offers nearly close-fitting and is less biased to commit overfitting. Every layer accepts guidance from the loss function through the shortcut paths that provide consistent deep supervision. As a result, DenseNet can be considered as a natural fit for per-pixel prediction problems.

3.4.2. MobielNet

MobileNet (Howard et al. 2017) is constructed with MobileNetV1 (Waheed et al. 2020) and MobileNetV2 (Sandler et al. 2018). This architecture has generally fitted that requires and performs with low computational power, i.e., mobile devices with low computational power (Sandler et al. 2018). Besides that, MobileNetv2 refers to depth-wise separated convolutions rather than standard convolution, demanding less computational power.

3.4.3. VGGNet architecture

VGGNet upgraded form of AlexNet (Jiang et al. 2019) developed with 13 convolutional layers with five max-pooling layers followed by three dense layers. The model can be considered highly efficient however it demands higher time consumption during model implementation. Moreover, VGGNet is associated with VGG16 and VGG19, where VGG19 is the advanced shape VGG16 (Qassim, Verma, and Feinzimer 2018), (Noon et al. 2020).

3.4.4. Xception

Xception arises from the Inception architectures, which supports replacement employing depth-wise separable convolutions (Dhillon and Verma 2019). It contains a practically indistinguishable parameter sum similar to the Inception-v1 model. In addition, convolution and pooling are applied in order to obtain automatic extraction and features reduction. The convolution affords an explication for determining the images and parameter distribution that reduces the model complexity. In contrast, pooling seems like a means of decreasing the features.

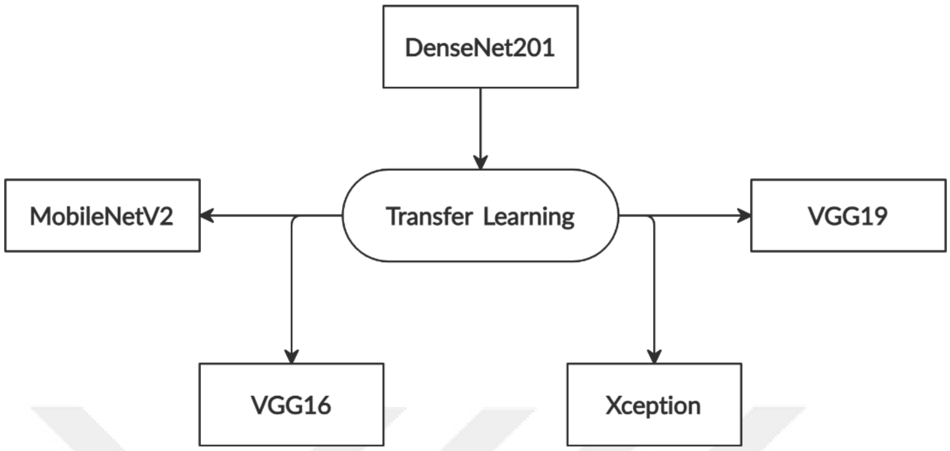


Figure 3.8. Various architectures of Transfer Learning

3.5. Deep Learning Framework: TensorFlow

TensorFlow is a commonly practiced library in the DL framework that enabling users to use DL externally significant concern of programming model (Pattanayak 2017). It is an open-source computing structure of Google that carries DL algorithms, including CNN, RNN, GAN and other variants that can be practiced on Linux, Windows and Mac platforms. TensorFlow has remarkable services, including exceptional adaptability, true portability, multi-language support, a grand algorithm library, and excellent documentation. TensorFlow provides a rich set of deep learning application programming interfaces (API), including basic vector-matrix calculations, optimization algorithms, CNN, RNN, and visual aids. TensorFlow utilizes dataflow designs to represent computation, shared events, and the operations that mutate events. It outlines the nodes of a dataflow chart across multiple computational schemes, such as general-purpose GPUS, multi-core CPUs, and custom-designed ASICs known as Tensor Processing Units (TPUS)

4. MERIALS AND METHODS

4.1. Dataset Description

For research purposes, the V2 Plant Seedlings Dataset (Giselsson et al. 2017) has been preferred to generate an efficient architecture for weeds detection. In addition, the applied dataset has 5,539 images and 960 unique plants belong to 12 species at several growth stages. Each class comprise different number of images as shown in Figure 9. The dimension of the complete dataset is 1.7 GB, where the physical resolution of dataset images is roughly 10 pixels per mm. The samples of each class are illustrated in Figure 10.

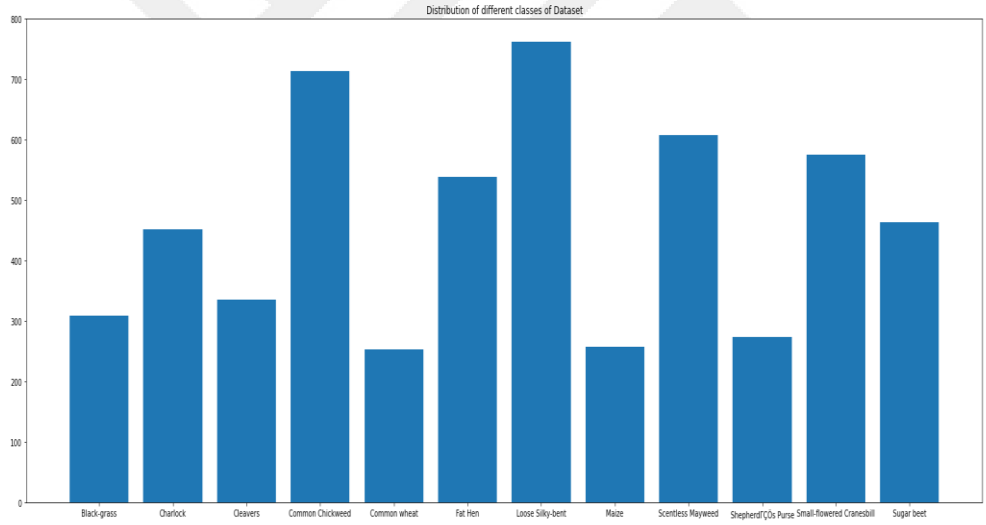


Figure 4.1. The unbalanced distribution of the dataset images in classes.

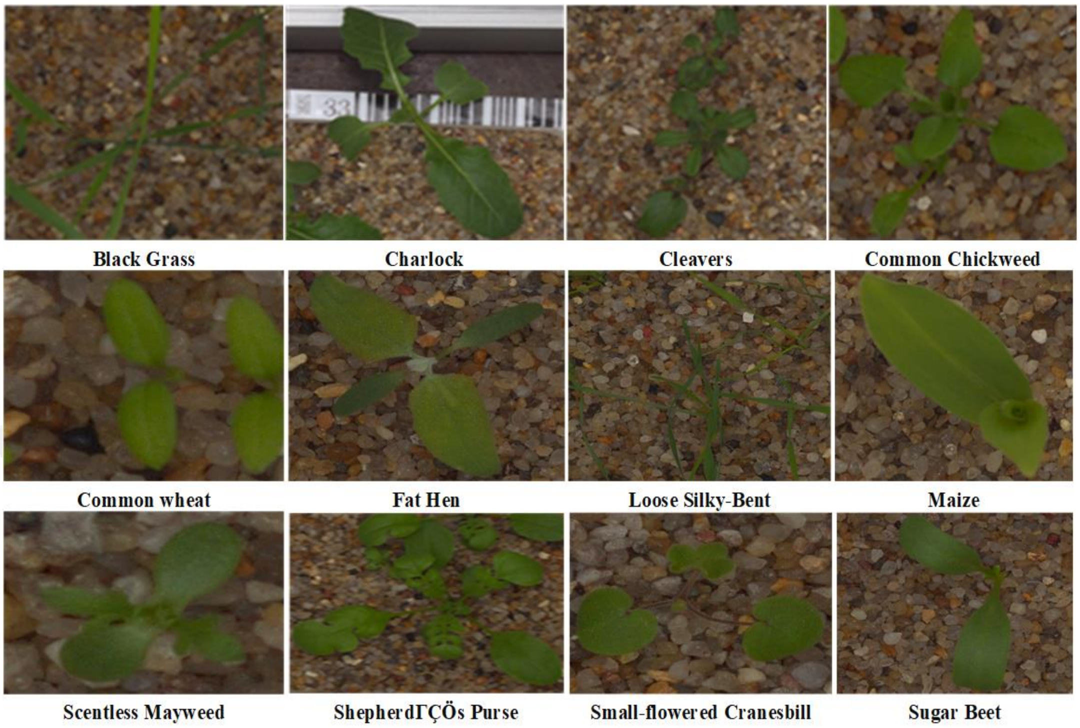


Figure 4.2**.** Sample images of the Plant Seedlings dataset belongs to 12 species

4.2. Model architecture: CovWNET

4.2.1. Preprocessing of CovWNET

Also, weeds dataset has an unbalanced distribution of classes as shown in Figure 9. It has been shown that the Common wheat Class contains 253 images that are the lowest number of images compared to the rest of the classes. In that case, 250 images are considered for each class; therefore, each class of image data is formed to have same number of images to prevent the inconsistency of dataset classes. As a result, the number of images in the dataset is decreased during the preprocessing of the proposed model. The complete preprocessing system of CovWNET is illustrated in Figure 11. In addition, the dataset was extracted as 90% for the training set and the rest of 10% for validation, test, i.e., 2700 and

300, respectively. During the training, overfitting has occurred; therefore, data augmentation has been applied to sort out the issues of overfitting.

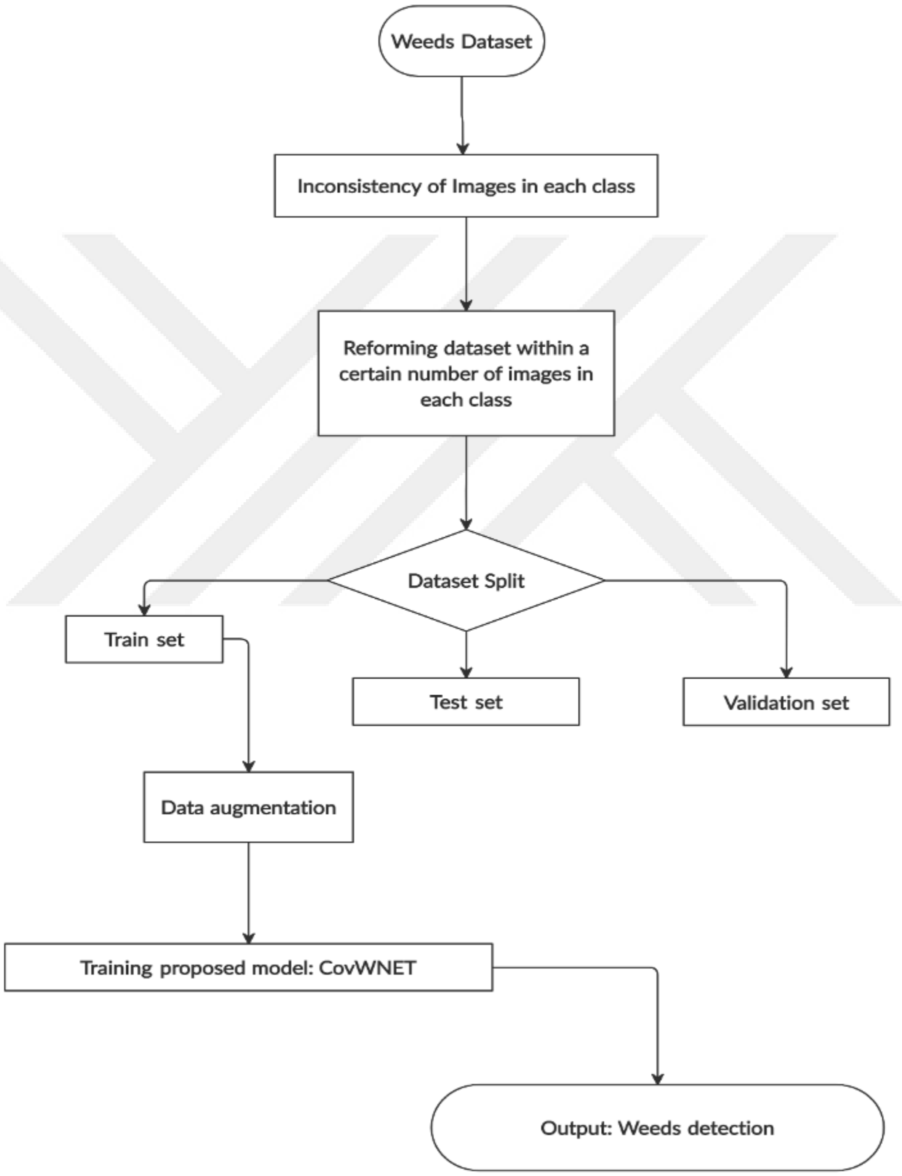


Figure 4.3**.** Step by step data preprocessing of CovWNET architecture

4.2.2. CovWNET Architecture

The proposed Convolutional Network for Weed Detection model is referred to as CovWNET, consisting of five 2D convolutional layers followed by three fully connected layers. Table 1 presents the proposed model summary in Keras format. Each 2D convolution layers have nonidentical filters with the kernel size of 3×3. The number of filters is 48, 64, 84, 65, and 84. Max pooling layer is applied after each convolutional layer with a 2x2 window and a stride of 2. Dropout layers are put together after each combination of convolution and max-pooling layers. The first and second layers use a dropout rate of 0.08, considering 0.20, 0.10, and 0.12 are applied to the rest of the layers. Afterward, a flatten layer is used to convert the resulted tensor to vector. Following fully connected layers consists of 512, 264, and 85 nodes. The dropout probability after each fully connected layer is 0.04. ReLU activation function is applied to entire convolutional and fully connected layers except the final fully connected layer since a SoftMax activation function is applied. The total number of parameters and the number of learnable parameters is 3,348,702.

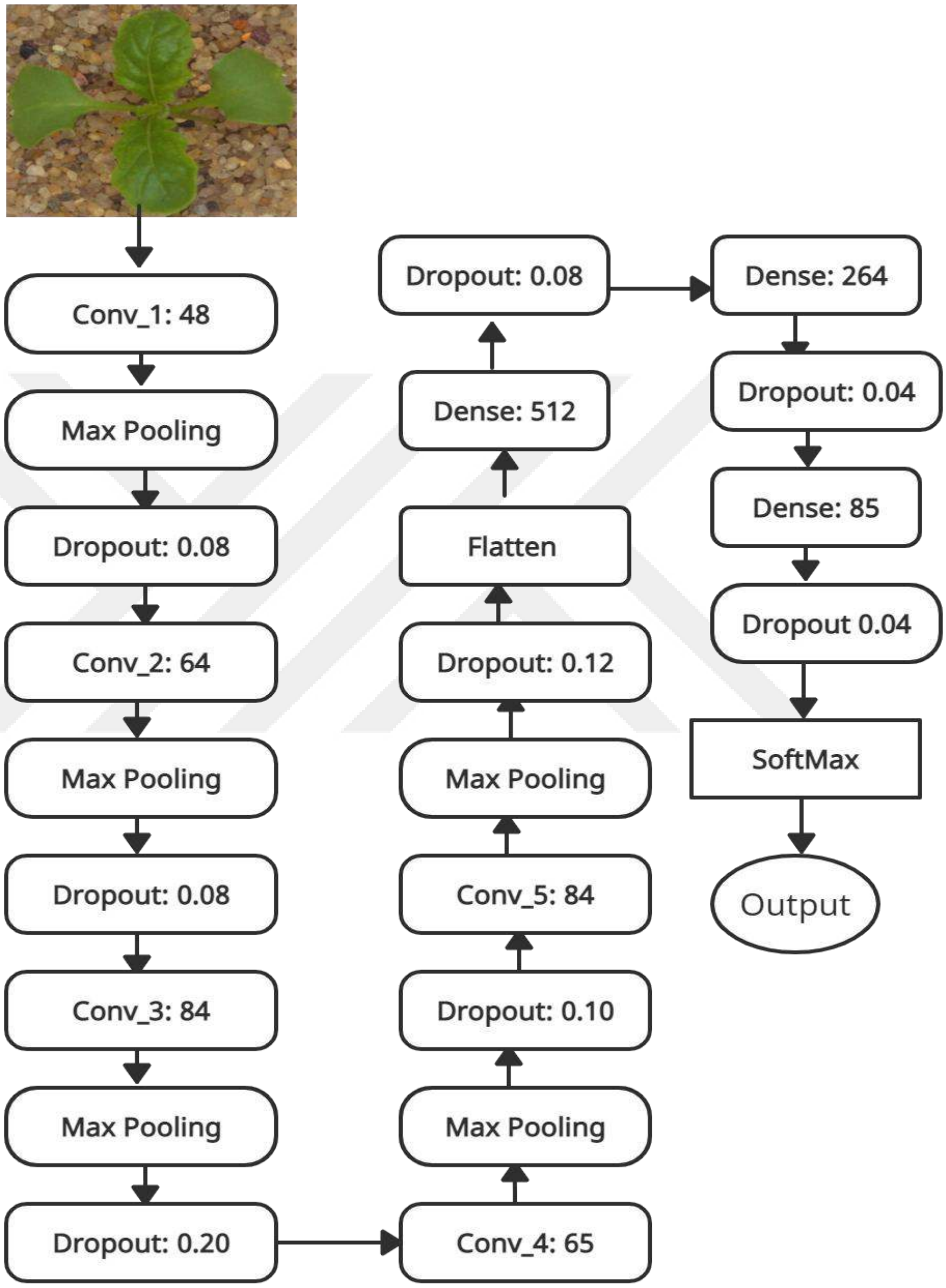


Figure 4.4. CovWNET architecture

Table 4.1. Summary of CovWNET architecture

Types of layers	Output configuration	Number of parameters
conv2d (Conv2D)	(None, 256, 256, 48)	1344
max_pooling2d (MaxPooling2D)	(None, 128, 128, 48)	0
dropout (Dropout)	(None, 128, 128, 48)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	27712
max_pooling2d_1 (MaxPooling2	(None, 64, 64, 64)	0
dropout_1 (Dropout)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 84)	134484
max_pooling2d_2 (MaxPooling2)	(None, 32, 32, 84)	0
dropout_2 (Dropout)	(None, 32, 32, 84)	0
conv2d_3 (Conv2D)	(None, 32, 32, 65)	(136565
max_pooling2d_3 (MaxPooling2)	(None, 16, 16, 65)	0
dropout_3 (Dropout)	(None, 16, 16, 65)	0
conv2d_4 (Conv2D)	(None, 16, 16, 84)	136584
max_pooling2d_4 (MaxPooling2)	(None, 8, 8, 84)	0
dropout_4 (Dropout)	(None, 8, 8, 84)	0
flatten (Flatten)	(None, 5376)	0
dense (Dense)	(None, 512)	2753024
dropout_5 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 264)	135432
dropout_6 (Dropout)	(None, 264)	0
dense_2 (Dense)	(None, 85)	22525
dropout_7 (Dropout)	(None, 85)	0
dense_3 (Dense)	(None, 12)	1032

4.2.3. Data Augmentation

Data augmentation is an effective strategy used in deep learning to increase the size and diversity of data by generating new samples using existing ones (Dyk and Meng 2012). Besides that, it has a regularization effect; thus, it helps avert overfitting and makes the dataset worthy. Before applying data augmentation, the dataset was segmented into training, validation, and test with a ratio of 90% and 10%, respectively. In the end, data augmentation addressed the training set and regenerated the number of images into the training set to 15,900. Table 2 presents the total amount of images before and after augmentation.

Table 4.2. Total number of images before and after data augmentation technique

Name of Classes	**Total number of images**	**Identical number of images**	**Number of train images**	**Total Train Images after augmentation**
Black-grass	309	250	225	1552
Charlock	452	250	225	1551
Cleavers	335	250	225	1545
Common Chickweed	713	250	225	1556
Common wheat	253	250	225	1543
Fat Hen	538	250	225	1557
Loose Silky-bent	762	250	225	1544
Maize	257	250	225	1541
Scentless Mayweed	607	250	225	1546
ShepherdΓÇÖs Purse	274	250	225	1556
Small-flowered Cranesbill	576	250	225	1553
Sugar beet	463	250	225	1556

4.3. Transfer Learning architecture

Fine-tuning transfer learning is applied to five several architectures in order to implement the research. As a result, each model consists of different layers with unique numbers of an epoch, batch size, and dropout. As a result, 60 epochs have been considered for each model. On the other hand, the batch size is 32, and 0.9 dropout rate are used. The entire dataset has been utilized for the implementation of fine-tuning transfer learning. Thus, the dataset is divided for each model as 90% and 10% for train, validation, and test set, respectively. Data augmentation was also applied for each model for acquiring the best result from a unique architecture.

Moreover, DenseNet201 is formed with a filter size of 1024, where its input size is 3x60x60 with 18,321,984 parameters. On the other hand, MobileNetV2 and VGG16 consist of 2x768 filters where the input shape is 3x224x224 with 2,257,984 and 14,714,688 parameters, respectively. Nevertheless, VGG19 consists of an input shape of 3x75x75 with a filter size is 2x768 with 20,024,384 parameters. In contrast, Xception is consisted with highest number of parameters i.e., 20,861,480. The input and filter size of Xception are 3 x 71 x 71 and 1 x 512 respectively.

4.4. Experimental Setup

In this research, the performance of the CovWNET network is compared with the performance of the state-of-the-art networks of transfer learning. The test networks are implemented using the TensorFlow Keras framework. Adam optimizer is used in the training step, and all of the applied models are trained from scratch using only the weed dataset. The learning rate for the proposed model is set to a default value of 0.001 and tuned to 0.0004 for achieving better accuracy. The learning rates of the other networks are not modified.

The complete experiments were performed over Google's Collaboratory platform. At the time of the experiments, the platform draws Tesla T4 GPU with 2496 CUDA cores, 12.69 GB RAM, and compute ability is reported as 7.

5. RESULT

After the preprocessing and applying of data augmentation, the proposed CovWNET model is retrained. Various losses have been initiated throughout the training phase that denotes the accuracy of model metrics are precise shown in Figure 12. During the implementation of CovWNET the dataset gets 100% accuracy into the training phase whereas 94% of the accuracy of validation and 91.33% accuracy of test set. The model is trained from scratch for 60 epochs with a batch size of 32. Performance metrics such as precision, recall, F1-score and support are calculated and reported in Table 3.

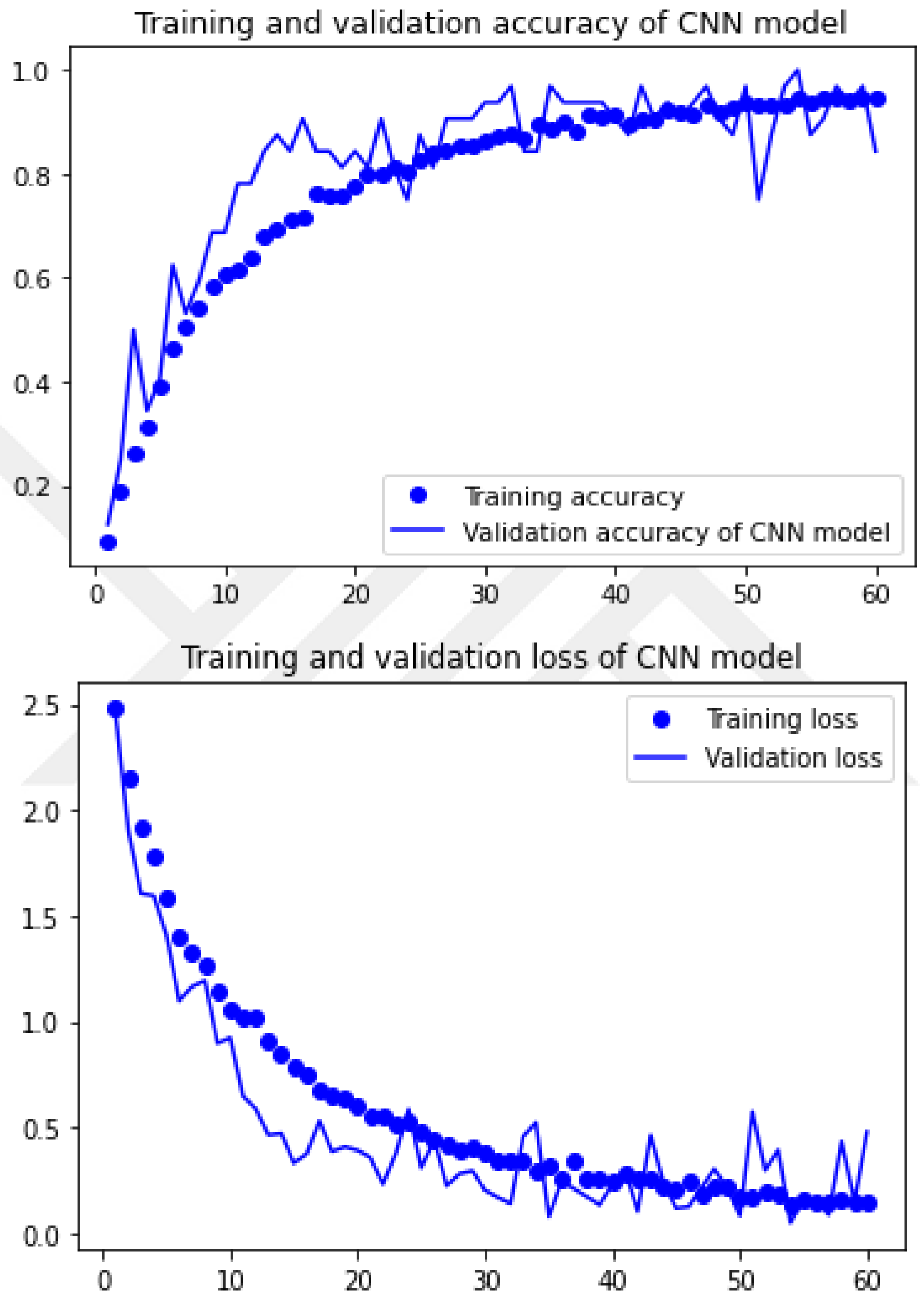
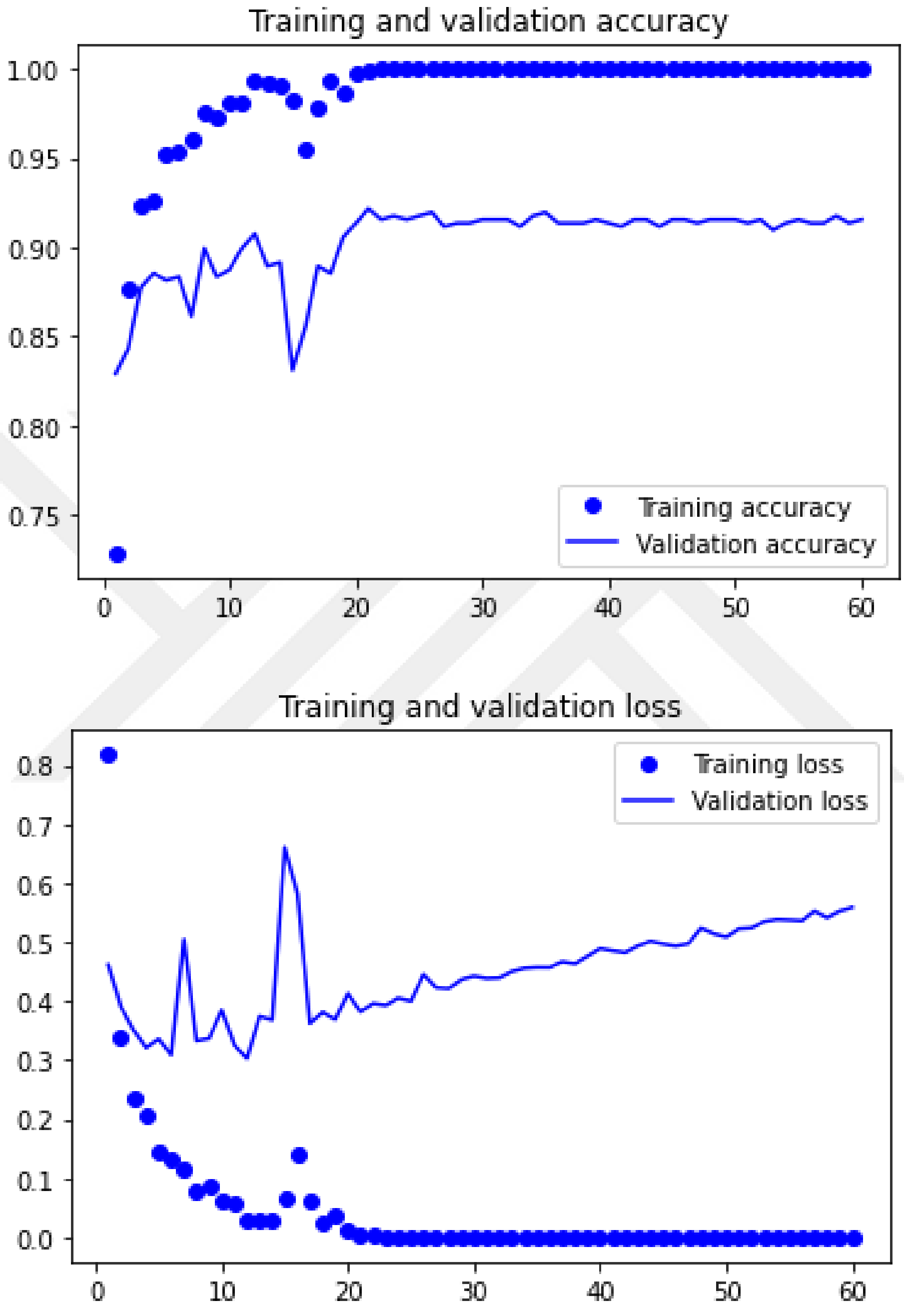


Figure 5.1. Training and validation accuracy and losses of CovWNET

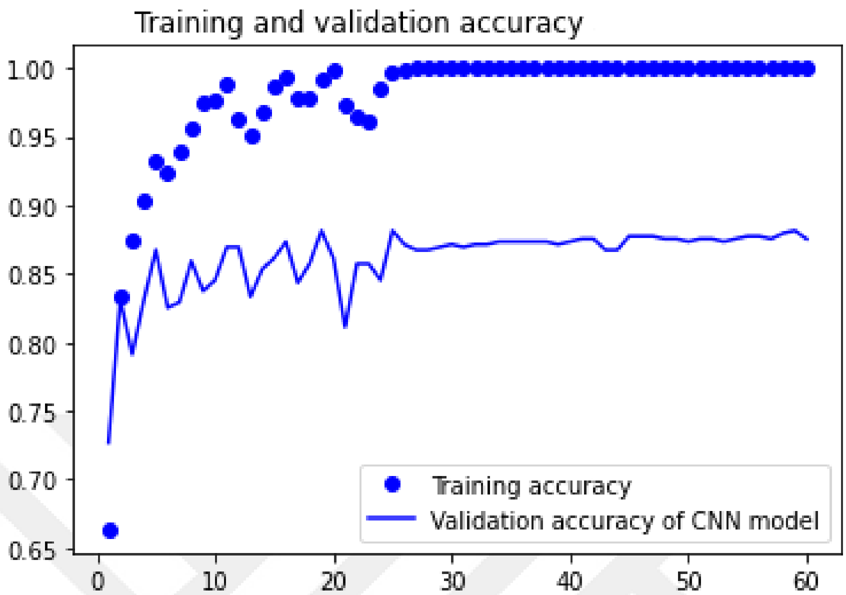
Table 5.1 Comparison based on performance metrics of CovWNET

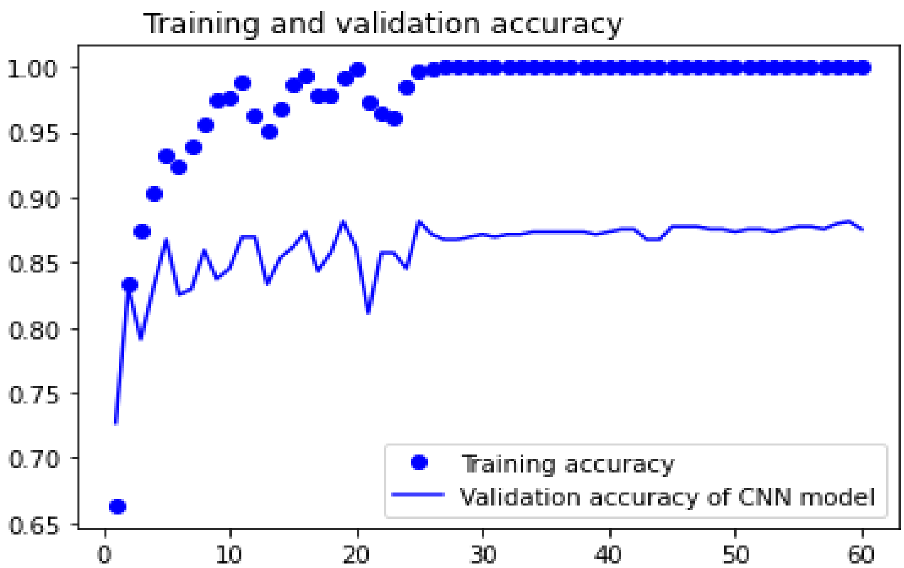
Name of classes	Metrics name			
	Precision	Recall	*F1*-score	Support
Black-grass	0.84	0.84	0.84	25
Charlock	1.00	0.92	0.96	25
Cleavers	0.82	0.92	0.87	25
Common Chickweed	0.92	0.96	0.94	25
Common wheat	0.83	0.96	0.89	25
Fat Hen	1.00	0.88	0.94	25
Loose Silky-bent	0.96	0.88	0.92	25
Maize	0.96	0.96	0.96	25
Scentless Mayweed	0.88	0.84	0.86	25
ShepherdΓÇÖs Purse	0.95	0.84	0.89	25
Small-flowered Cranesbill	1.00	0.96	0.98	25
Sugar beet	0.86	1.00	0.93	25

In addition, transfer learning with fine-tuning is carried out by gradually unfreezing layers. In order to perform transfer learning, DenseNet201, MobileNetV2, VGG16, VGG19, Xception have been considered. All of the models trained with a 100% accuracy whereabouts validation phase generated divergent aftereffects from the train set domain. The DenseNet201 achieved the best accuracy, 93%, with 18,321,984 parameters among applied architectures. MobileNet obtained 88.5% with 2,257,984 parameters. The VGG16 and VGG19 achieved gradually 89% and 89.4%, with 14,714,688 and 20,024,384 parameters, whereas Xception acquires 86.3% with 20,861,480 parameters. Variation of training and validation accuracy and losses are shown in Figure 13(a-e). Each architecture of transfer learning performance metrics such as precision, recall, F1-score and support are calculated and reported in Table 4 to 8.

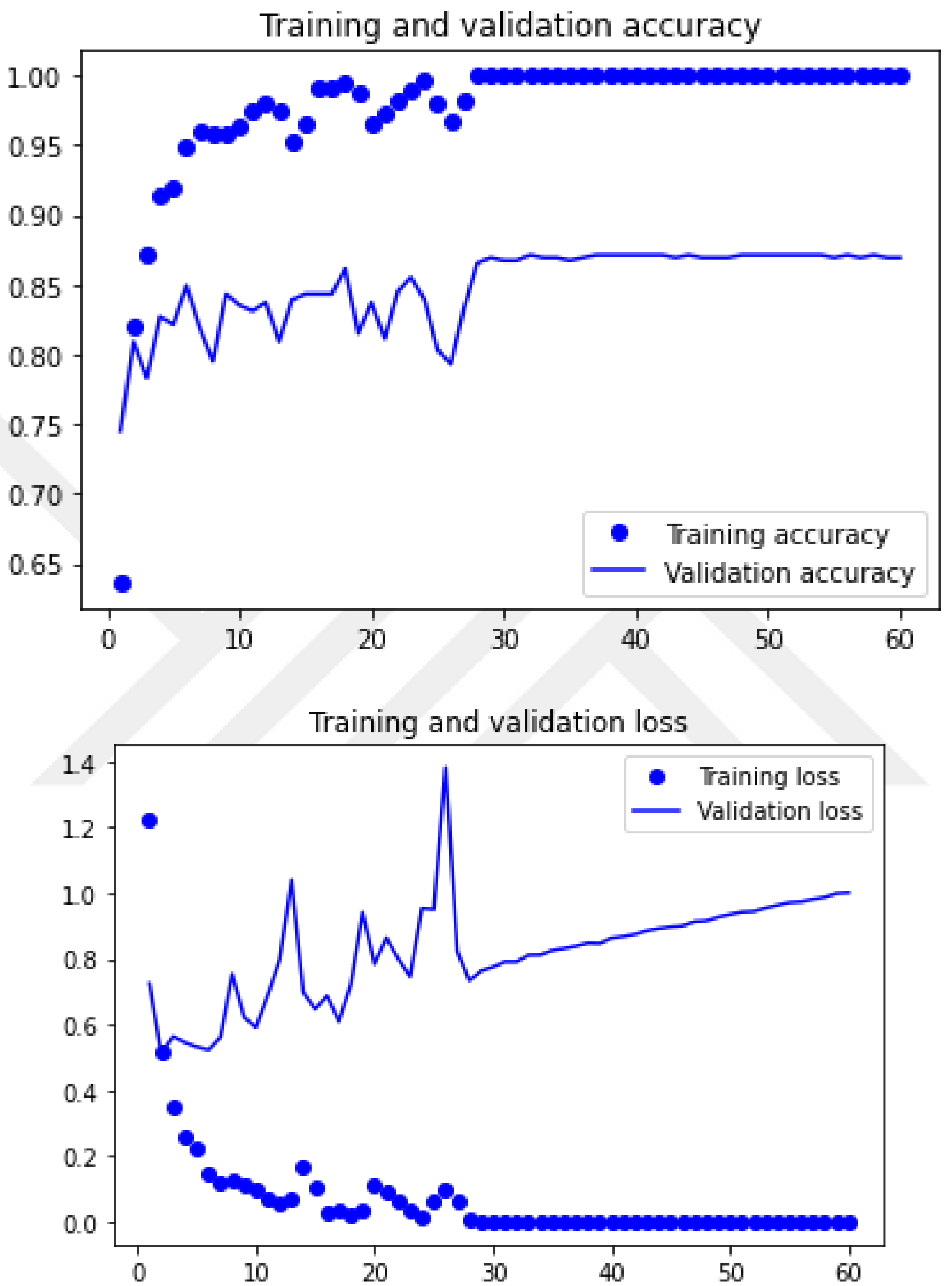


(a) DenseNet201 model

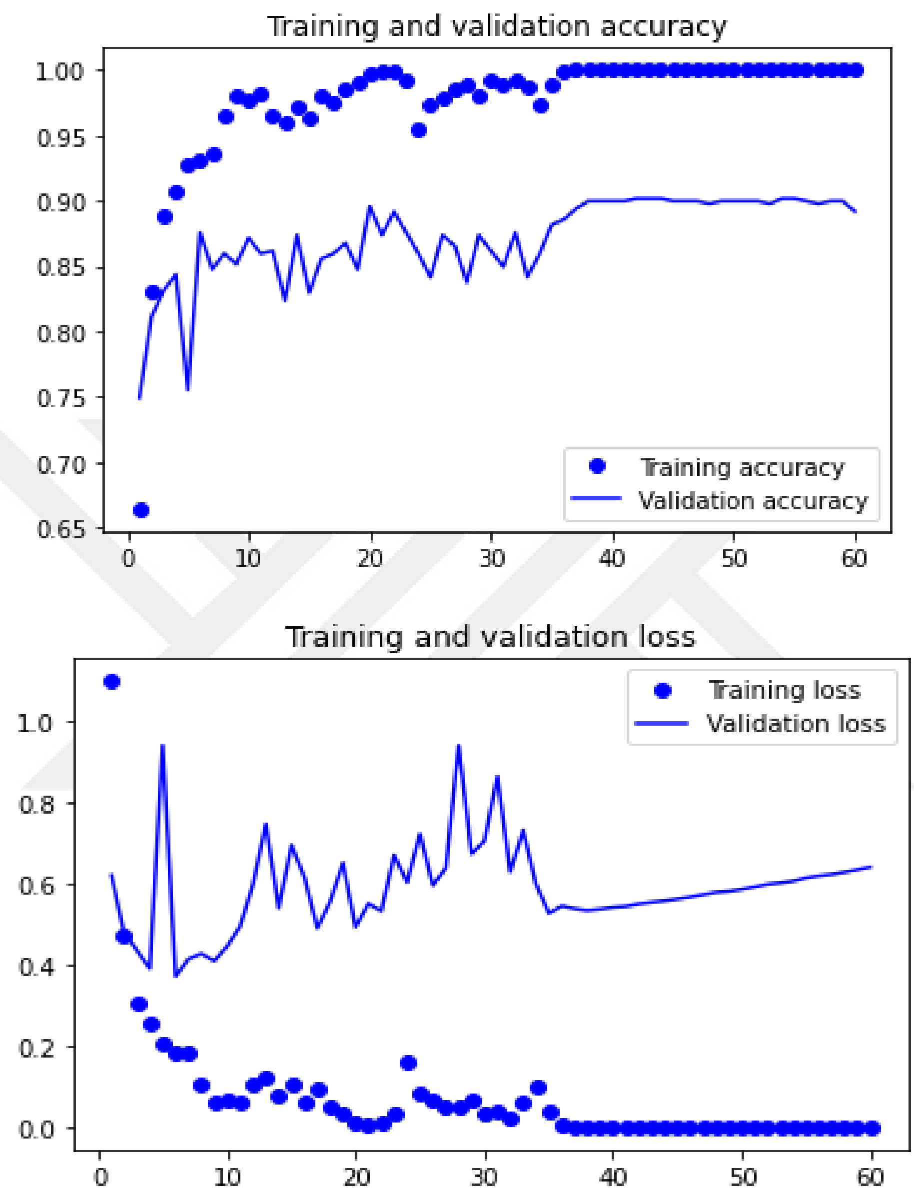




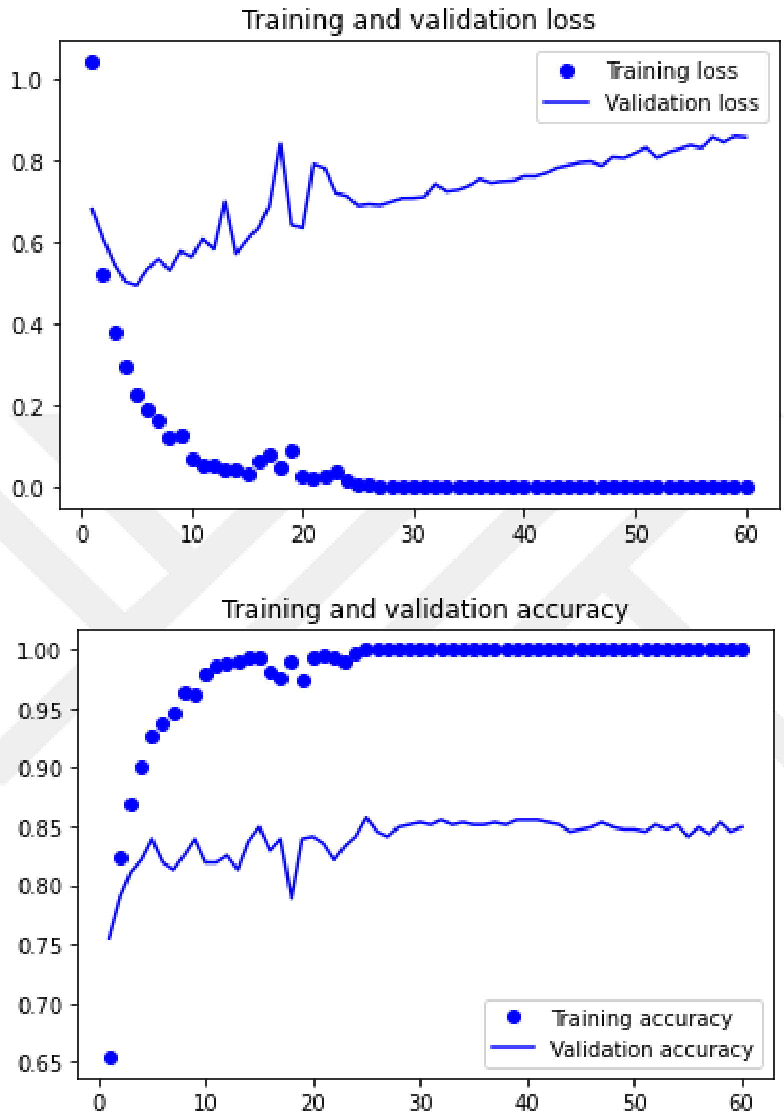
(b) MobileNetV2 model



(c) VGG16 model



(d) VGG19 model



(e) Xception model

Figure 5.2. (a - e) Training and validation accuracy and losses of fine-tuning transfer learning models.

Table 52. DenseNet201 Model

DenseNet201 Model				
Name of classes	**Metrics name**			
	Precision	**Recall**	***F1*-score**	**Support**
Black-grass	0.72	0.60	0.66	35
Charlock	0.95	0.98	0.96	41
Cleavers	1.00	0.94	0.97	35
Common Chickweed	1.00	0.99	0.99	74
Common wheat	0.95	1.00	0.98	20
Fat Hen	0.95	0.92	0.93	62
Loose Silky-bent	0.80	0.90	0.85	78
Maize	1.00	1.00	1.00	14
Scentless Mayweed	0.98	0.95	0.97	60
ShepherdΓÇÖs Purse	0.94	0.91	0.92	32
Small-flowered Cranesbill	0.93	0.97	0.95	58
Sugar beet	0.96	0.98	0.97	45

Table 5.3. MobileNetV2 Model

MobileNetV2 Model				
Name of classes	**Metrics name**			
	Precision	**Recall**	***F1*-score**	**Support**
Black-grass	0.54	0.56	0.55	27
Charlock	0.91	0.88	0.90	34
Cleavers	0.79	0.91	0.85	34
Common Chickweed	0.92	0.91	0.91	74
Common wheat	0.90	0.87	0.88	30
Fat Hen	0.92	0.92	0.92	52
Loose Silky-bent	0.84	0.86	0.85	74
Maize	0.96	0.93	0.94	27
Scentless Mayweed	0.88	0.91	0.89	64
ShepherdΓÇÖs Purse	0.91	0.84	0.87	25
Small-flowered Cranesbill	0.97	0.93	0.95	61
Sugar beet	0.96	0.92	0.94	52

Table 5.4. VGG16 model

VGGNET16 Model				
Name of classes	**Metrics name**			
	Precision	**Recall**	***F1*-score**	**Support**
Black-grass	0.52	0.61	0.56	28
Charlock	1.00	1.00	1.00	43
Cleavers	0.97	0.94	0.95	33
Common Chickweed	0.95	0.94	0.95	65
Common wheat	0.79	0.81	0.80	27
Fat Hen	0.86	0.91	0.88	55
Loose Silky-bent	0.86	0.82	0.84	84
Maize	0.96	0.96	0.98	25
Scentless Mayweed	0.90	0.89	0.90	63
ShepherdΓÇÖs Purse	0.83	0.77	0.80	26
Small-flowered Cranesbill	0.95	0.95	0.95	55
Sugar beet	0.96	0.94	0.95	50

Table 5.5. VGG19 Model

VGGNET19 Model				
Name of classes	**Metrics name**			
	Precision	**Recall**	***F1*-score**	**Support**
Black-grass	0.70	0.59	0.64	27
Charlock	0.97	0.92	0.95	39
Cleavers	0.95	0.95	0.95	44
Common Chickweed	0.88	0.91	0.90	66
Common wheat	0.68	0.93	0.79	14
Fat Hen	0.97	0.92	0.94	62
Loose Silky-bent	0.85	0.85	0.85	65
Maize	0.96	0.87	0.91	30
Scentless Mayweed	0.84	0.92	0.88	64
ShepherdΓÇÖs Purse	0.81	0.73	0.77	30
Small-flowered Cranesbill	0.97	1.00	0.98	59
Sugar beet	0.93	0.93	0.93	54

Table 5.6. Xception Model

Xception Model				
Name of classes	**Metrics name**			
	Precision	**Recall**	***F1*-score**	**Support**
Black-grass	0.71	0.46	0.56	37
Charlock	0.96	0.94	0.95	51
Cleavers	0.94	0.91	0.93	34
Common Chickweed	0.87	0.91	0.89	66
Common wheat	0.75	0.78	0.77	23
Fat Hen	0.91	0.89	0.90	56
Loose Silky-bent	0.80	0.87	0.84	79
Maize	0.86	0.96	0.91	25
Scentless Mayweed	0.88	0.89	0.88	56
ShepherdΓÇÖs Purse	0.73	0.67	0.70	24
Small-flowered Cranesbill	0.90	0.98	0.94	53
Sugar beet	0.92	0.88	0.90	50

5.1. Comparison

After the successful training runs for the aforementioned implementations, it substantiated that the maximum test accuracy was achieved by DenseNet201 architecture. However, CovWNET and MobileNetV2 performed with lower parameters rest of the applied model. In addition, compared with MobileNetV2, CovWNET achieved more than 2.8% test accuracy with more than 1.5% parameters. On the other hand, CovWNET obtained 2.3% and 1.9% better results than VGG16 and VGG19, respectively, with approximately 4.4% and 7% lower parameters. Besides that, Xception performed with the most extensive parameters and acquired 5% less accuracy than CovWNET, whereas CovWNET achieved approximately

1.7% less accuracy with 6% lower parameters than DenseNet201. A complete comparison of the implemented models is illustrated in the Table 9.

Table 5.7. Comparisons based on accuracy

Model	Parameters	Test accuracy
CovWNET	3,348,702	91.3%
DenseNet201	18,321,984	93.0%
MobileNetV2	2,257,984	88.5%
VGG16	14,714,688	89.0%
VGG19	20,024,384	89.4%
Xception	20,861,480	86.3%

5.2. Discussion

This thesis aims to investigate the new opportunities to examine the use of recent and robust applications of AI to support sustainable expansion in agriculture. Similarly, it can be said that the fundamental objective of this thesis is to contribute to the goal of transforming the field of primitive agriculture into digital agriculture. As a result, crop weeds detection and classification have been generated, which is necessary to promote crop stability and inhibit weed breach to achieve highly efficient weed management when proficient expertise is unavailable. The DL models that can fit into a mobile device became the main focus of this study. Therefore, the state-of-the-art DL models and transfer learning methods were applied Unquestionably, the outcomes mentioned above illustrate the inherent appropriateness of utilizing CNN models for weeds crop detection and identification. In addition, DL methods are practiced to multiple challenges of agricultural and vegetable cultivation in order to identify the harmful fact, i.e., weeds. Instead, DL can precisely determine agricultural emergencies, the distinct forms and structures employed, the sources, the quality and the preceding processing of the data used, and the overall production produced according to the metrics applied in work.

The greatest aspiration was to attain the configuration that allowed the best appearance according to the evaluation standards. The proposed novel DL network CovWNET consists of 3,348,702 parameters, which is quite small considering the competition. In previous work, researchers did not develop a dedicated CNN model for the weed detection problem. They use well-studied networks of that exist in DL toolbox. For example, ResNET, GoogleNET, AlexNET were popular choices. Additionally, some research also tried to combine AlexNET and VGGNET (Chavan and Nandedkar 2018). Though the accuracy of AgroAVNET is higher than CovWNET, it is significantly more “complex than CovWNET. In addition, transfer learning with fine-tuning architectures is commonly used for weeds classification and detection, i.e., VGGNET, ResNet.

Nevertheless, DenseNet201 is also rarely used for this purpose, where the DenseNet201 algorithm obtained the most reliable performance with a 93% accuracy, alongside a moderate contrast between train and test set. It can be said that the result of DenseNet201 is mostly higher than the previous work of (Ofori and El-Gayar 2020). On the other hand, in (Mamani Diaz, Medina Castaneda, and Mugruza Vassallo 2019), they have obtained the best result in their research by Xception was 86.2% and for VGGNET was 76.60 that is absolutely lowest as compared then the result of current thesis. Comprehensively, it can be observed that the thesis conclusion is better than the average representation of DenseNet201 92.21% presented by CNN crop weed detection and classification (Ofori and El-Gayar 2020). On the other, CovWNET also deserves a sustainable place since it is simpler and lowest parameter than the other novel model.

In the research investigation, it can be located that several misclassifications occurred between Black-grass, Common chickweed, Common wheat, Loose silky-bent, and Scentless mayweed in VGG16 and Xception model. Furthermore, the purpose is to identify crops from weeds utmost of the networks would have easily achieved an average above 100% accuracy (maximum accuracy). Hence, if it can be served for more useful biochemical factors with more precious biodegradability and lower environmental constancy, that accuracy and outcomes cover the process for additional digital conversion, including innovative technology abilities to assure sustainable growth in SA. The figure of confusion matrix and weeds classification with misclassification shown in Figure 14 to 25.

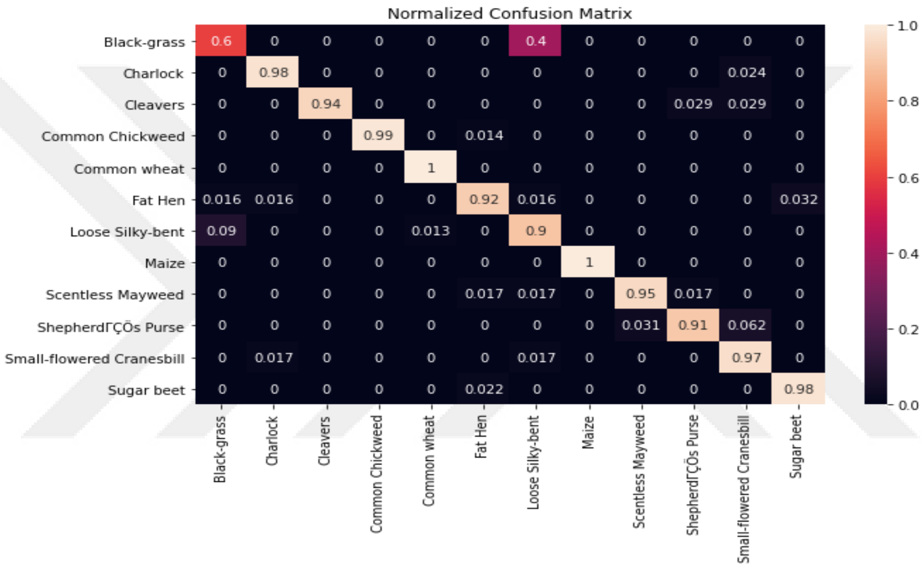


Figure 5.3. Confusion matrix of DenseNet201 architecture

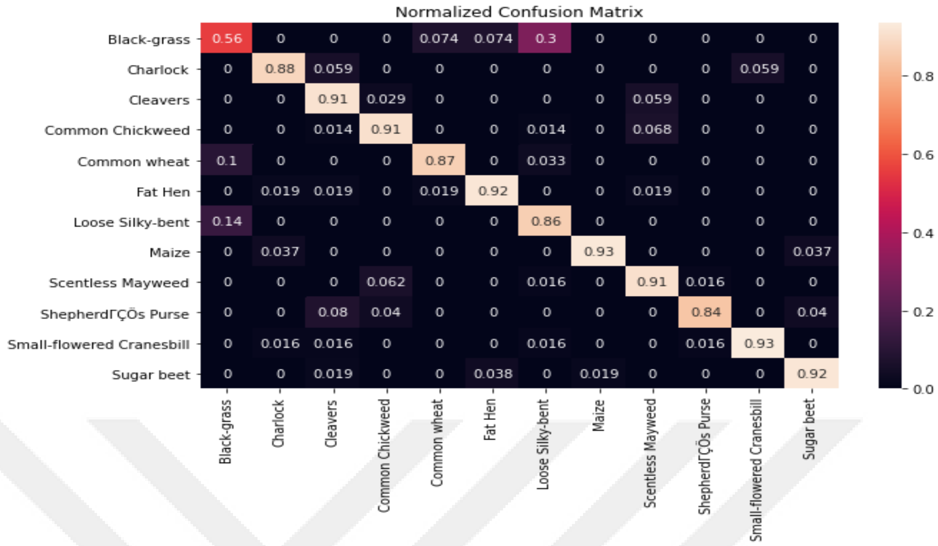


Figure 5.4. Confusion matrix of MobileNetV2 architecture

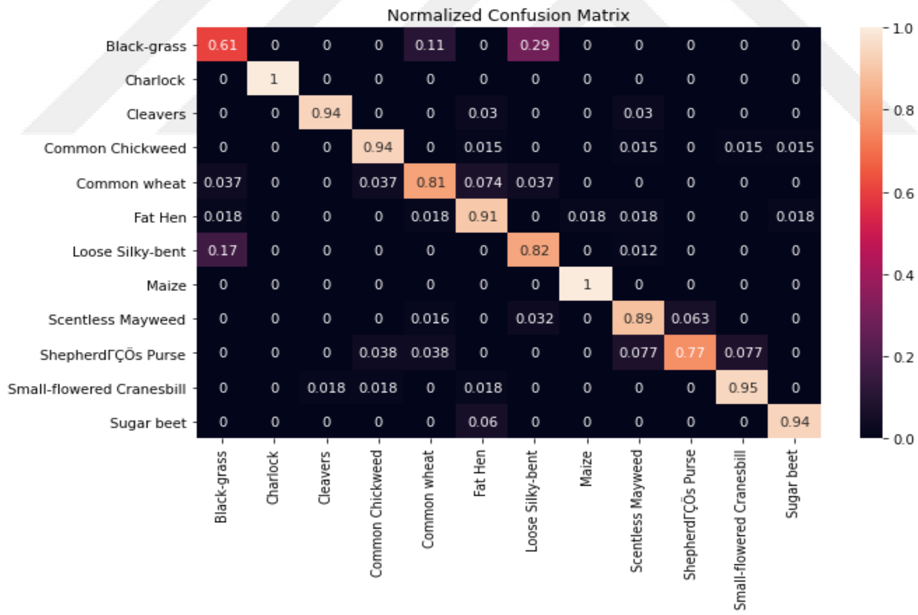


Figure 5.5. Confusion matrix of VGG16 architecture

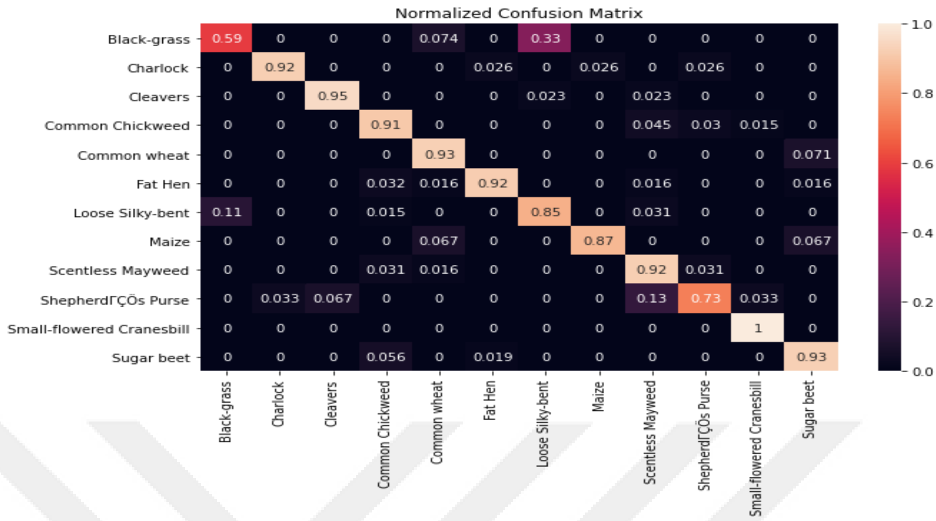


Figure 5.6. Confusion matrix of VGG19 architecture

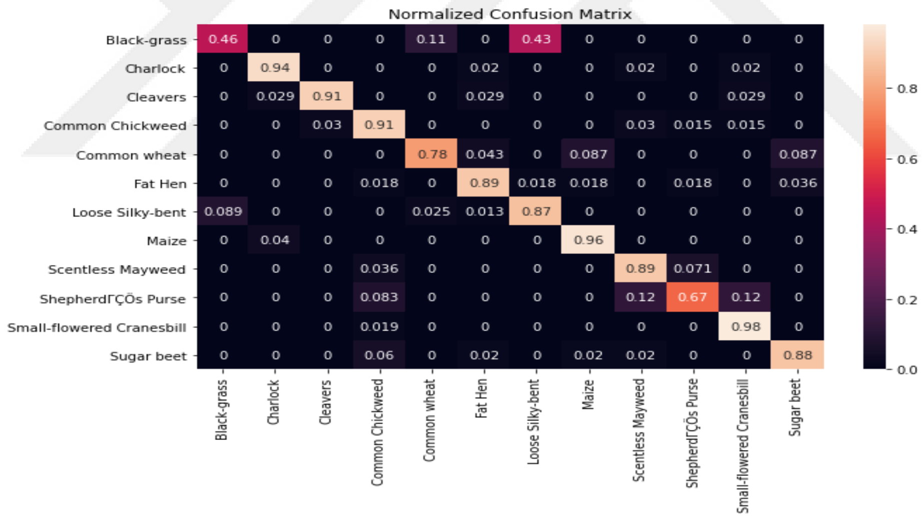


Figure 5.7. Confusion matrix of Xception architecture

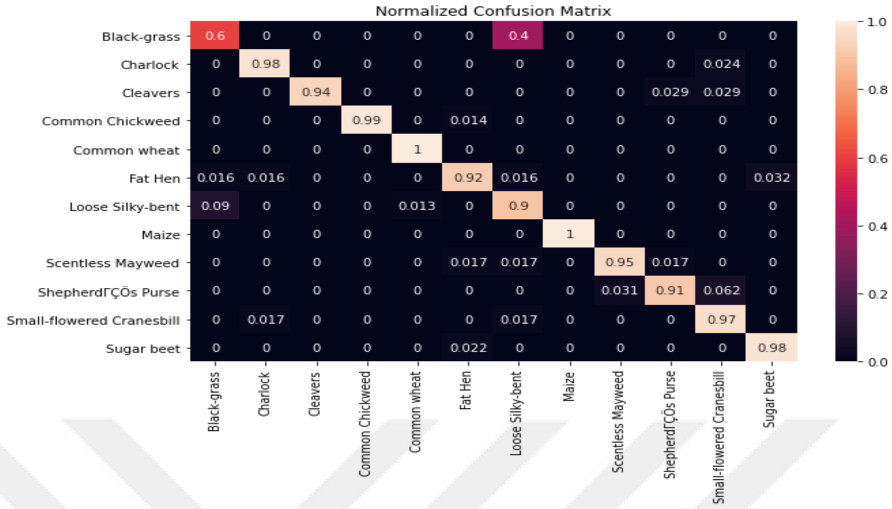


Figure 5.8. Confusion matrix of CovWNET architecture

Figure 5.9. Weeds classification of DenseNet201

Figure 5.10**.** Weeds classification of MobileNetV2 architecture

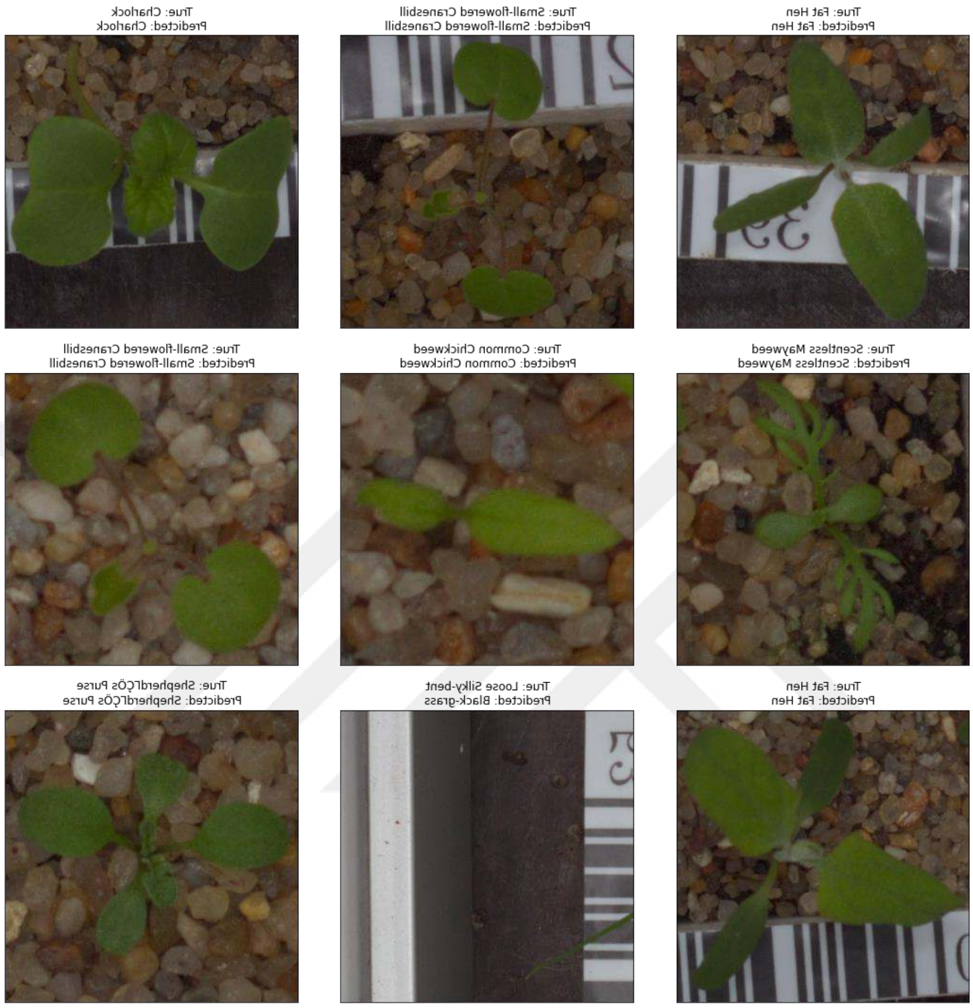


Figure 5.11**.** Weeds classification of VGG16 architecture

Figure 5.12. Weeds classification of VGG19 architecture

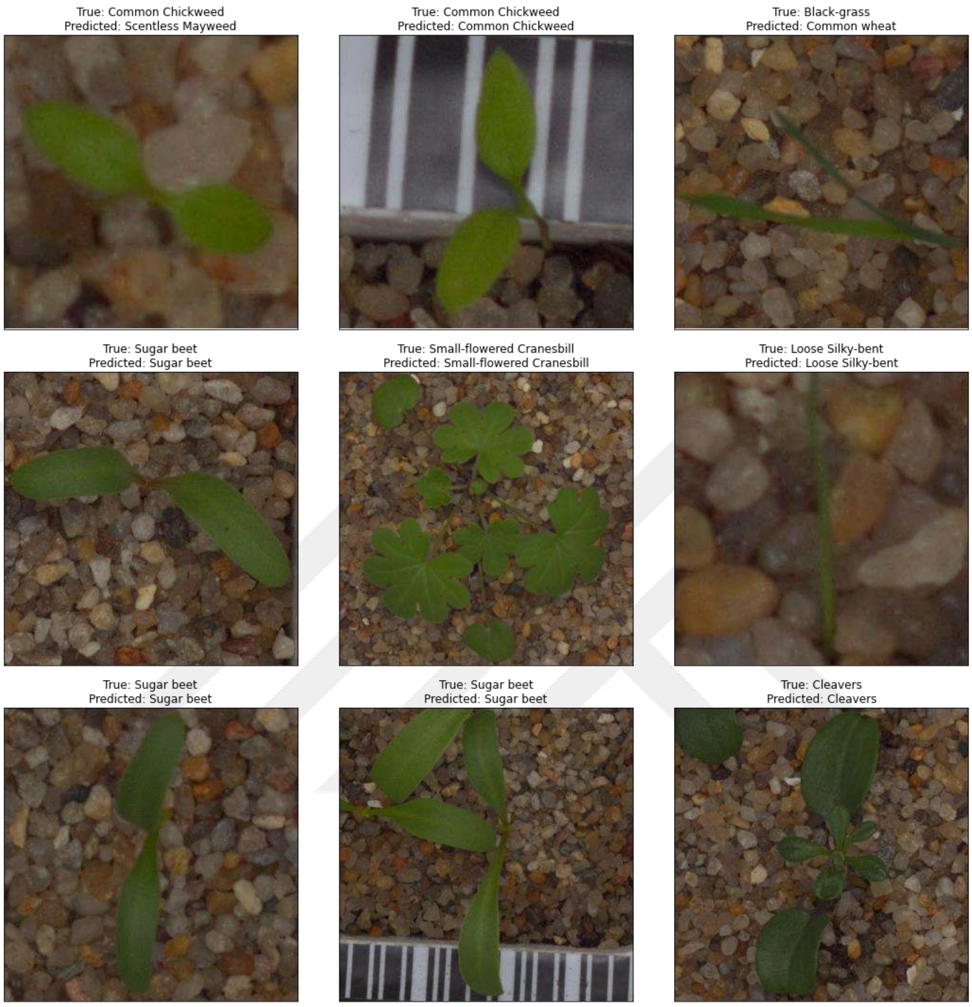


Figure 5.13. Figure 24 Weeds classification of Xception architecture

Figure 5.14. Weeds classification of CovWNET architecture

6. CONCLUSION

Weeds and crop classification makes a significant contribution to discriminate weeds and plants into the agricultural fields. It also assists in developing the automated framework for the weed divergence process. Therefore, a novel CNN model that refers to CovWNET is proposed in this thesis to detect and classify twelve different types of weeds. In addition, a state-of-art transfer learning model is trained to assimilate their results between CovWNET. The applied transfer learning models are DenseNet201, MobileNetV2, VGG16, VGG19, and Xception. The plant seedling dataset has been considered for preparing an ideal weeds classification and detection model. The dataset consists of 5,539 images and is distributed within twelve classes.

The overall results introduce a promising approach for the weeds detection and classification process. According to the evaluation of applied models, though DenseNet201 achieved the highest prediction accuracy, eventually, CovWNET accomplished further maximum accuracy with the immensely lowest parameters. Alternatively, MobileNetV2 consumes the overall lowest parameters; nevertheless, it has deficient accuracy compared to the CovWNET. In the fullness of time, the proposed network is designed with the help of the TensorFlow and Keras library. The network has a limited number of parameters and achieved a significant accuracy in tests compared to the implementations obtained by transfer learning.

The future work will generate novel architectures that can be considered in crops behavior identification and their conditions by applying an artificial intelligence framework. On the other hand, the lack of an appropriate dataset, resources with hardware implementation, i.e., required sensor, is a significant challenge for novel research. The collection of real-time data directly from the agricultural field contributes to intelligent agriculture and assists the farmers as their requirements. In the end, we recommend the creation of more accessible resources for precision agriculture research.

REFERENCES

Abdar, Moloud et al. 2021. “A Review of Uncertainty Quantification in Deep Learning: Techniques, Applications and Challenges.” *Information Fusion* 76: 243–97.

“Agriculture Overview.” https://www.worldbank.org/en/topic/agriculture/overview (July 25, 2021).

Ahmad, Aanis et al. 2021. “Performance of Deep Learning Models for Classifying and Detecting Common Weeds in Corn and Soybean Production Systems.” *Computers and Electronics in Agriculture* 184: 106081.

Ahmed, Faisal et al. 2012. “Classification of Crops and Weeds from Digital Images: A Support Vector Machine Approach.” *Crop Protection* 40: 98–104.

Bah, M. Dian, Eric Dericquebourg, Adel Hafiane, and Raphael Canals. 2018. “Deep Learning Based Classification System for Identifying Weeds Using High-Resolution UAV Imagery.” *Advances in Intelligent Systems and Computing* 857: 176–87. https://link.springer.com/chapter/10.1007/978-3-030-01177-2_13 (August 6, 2021).

Bah, M Dian, Adel Hafiane, and Raphael Canals. 2018. “Deep Learning with Unsupervised Data Labeling for Weed Detection in Line Crops in UAV Images.” *Remote Sensing 2018, Vol. 10, Page 1690* 10(11): 1690. https://www.mdpi.com/2072-4292/10/11/1690/htm (August 6, 2021).

Bakhshipour, Adel, and Abdolabbas Jafari. 2018. “Evaluation of Support Vector Machine and Artificial Neural Networks in Weed Detection Using Shape Features.” *Computers and Electronics in Agriculture* 145: 153–60.

Bera, Somenath, and Vimal K. Shrivastava. 2019. “Analysis of Various Optimizers on Deep Convolutional Neural Network Model in the Application of Hyperspectral Remote Sensing Image Classification.” *https://doi.org/10.1080/01431161.2019.1694725* 41(7): 2664–83. https://www.tandfonline.com/doi/abs/10.1080/01431161.2019.1694725 (July

23, 2021).

Berge, T. W., A. H. Aastveit, and H. Fykse. 2008. “Evaluation of an Algorithm for Automatic Detection of Broad-Leaved Weeds in Spring Cereals.” *Precision Agriculture 2008 9:6* 9(6): 391–405. https://link.springer.com/article/10.1007/s11119-008-9083-z (July 23, 2021).

Boyina, Lohitha et al. 2021. “Weed Detection in Broad Leaves Using Invariant U-Net Model.” : 1–4.

Chavan, Trupti R., and Abhijeet V. Nandedkar. 2018. “AgroAVNET for Crops and Weeds Classification: A Step Forward in Automatic Farming.” *Computers and Electronics in Agriculture* 154: 361–72.

Dai, Xiang, Youlin Xu, Jiaqiang Zheng, and Haichao Song. 2019. “Analysis of the Variability of Pesticide Concentration Downstream of Inline Mixers for Direct Nozzle Injection Systems.” *Biosystems Engineering* 180: 59–69.

Dhillon, Anamika, and Gyanendra K. Verma. 2019. “Convolutional Neural Network: A Review of Models, Methodologies and Applications to Object Detection.” *Progress in Artificial Intelligence 2019 9:2* 9(2): 85–112. https://link.springer.com/article/10.1007/s13748-019-00203-0 (July 23, 2021).

Dyk, David A van, and Xiao-Li Meng. 2012. “The Art of Data Augmentation.” *http://dx.doi.org/10.1198/10618600152418584* 10(1): 1–50. https://www.tandfonline.com/doi/abs/10.1198/10618600152418584 (September 15, 2021).

Giselsson, Thomas Mosgaard et al. 2017. “A Public Image Database for Benchmark of Plant Seedling Classification Algorithms.” https://arxiv.org/abs/1711.05458v1 (July 23, 2021).

Grigorescu, Sorin, Bogdan Trasnea, Tiberiu Cocias, and Gigel Macesanu. 2020. “A Survey of Deep Learning Techniques for Autonomous Driving.” *Journal of Field Robotics* 37(3): 362–86. https://onlinelibrary.wiley.com/doi/full/10.1002/rob.21918 (July 23, 2021).

Gu, Jiuxiang et al. 2018. “Recent Advances in Convolutional Neural Networks.”

Pattern Recognition 77: 354–77.

Guo, Yanming et al. 2016. "Deep Learning for Visual Understanding: A Review." *Neurocomputing* 187: 27–48.

Hasan, A. S.M.Mahmudul et al. 2021. "A Survey of Deep Learning Techniques for Weed Detection from Images." *Computers and Electronics in Agriculture* 184: 106067.

Howard, Andrew G. et al. 2017. "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications." https://arxiv.org/abs/1704.04861v1 (September 19, 2021).

Hu, Kun et al. 2020. "Graph Weeds Net: A Graph-Based Deep Learning Method for Weed Recognition." *Computers and Electronics in Agriculture* 174: 105520.

Islam, Nahina et al. 2021. "Early Weed Detection Using Image Processing and Machine Learning Techniques in an Australian Chilli Farm." *Agriculture 2021, Vol. 11, Page 387* 11(5): 387. https://www.mdpi.com/2077-0472/11/5/387/htm (August 6, 2021).

Jha, Kirtan, Aalap Doshi, Poojan Patel, and Manan Shah. 2019. "A Comprehensive Review on Automation in Agriculture Using Artificial Intelligence." *Artificial Intelligence in Agriculture* 2: 1–12.

Jiang, Bo et al. 2019. "Fusion of Machine Vision Technology and AlexNet-CNNs Deep Learning Network for the Detection of Postharvest Apple Pesticide Residues." *Artificial Intelligence in Agriculture* 1: 1–8.

Jin, Xiaojun, Jun Che, and Yong Chen. 2021. "Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation." *IEEE Access* 9: 10940–50.

Kamilaris, Andreas, and Francesc X. Prenafeta-Boldú. 2018. "Deep Learning in Agriculture: A Survey." *Computers and Electronics in Agriculture* 147: 70–90.

Karaca, Murat, and Sevda Serpil Dursun. 2020. "Possible Effects of Climate Change on Weeds in Agriculture." *Selcuk Journal of Agriculture and Food Sciences*

34(1): 111–17. http://sjafs.selcuk.edu.tr/sjafs/article/view/1145 (August 3, 2021).

Khan, Shahbaz, Muhammad Tufail, Muhammad Tahir Khan, Zubair Ahmad Khan, and Shahzad Anwar. 2021. “Deep Learning-Based Identification System of Weeds and Crops in Strawberry and Pea Fields for a Precision Agriculture Sprayer.” *Precision Agriculture 2021*: 1–17. https://link.springer.com/article/10.1007/s11119-021-09808-9 (August 6, 2021).

Khan, Shahbaz, Muhammad Tufail, Muhammad Tahir Khan, Zubair Ahmad Khan, Javaid Iqbal, et al. 2021. “Real-Time Recognition of Spraying Area for UAV Sprayers Using a Deep Learning Approach.” *PLOS ONE* 16(4): e0249436. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0249436 (August 6, 2021).

Liu, Jizhan, Irfan Abbas, and Rana Shahzad Noor. 2021. “Development of Deep Learning-Based Variable Rate Agrochemical Spraying System for Targeted Weeds Control in Strawberry Crop.” *Agronomy 2021, Vol. 11, Page 1480* 11(8): 1480. https://www.mdpi.com/2073-4395/11/8/1480/htm (August 6, 2021).

Lu, Ning et al. 2021. “MASTER: Multi-Aspect Non-Local Network for Scene Text Recognition.” *Pattern Recognition* 117: 107980.

Mamani Diaz, Carlos A., Edgar E. Medina Castaneda, and Carlos A. Mugruza Vassallo. 2019. “Deep Learning for Plant Classification in Precision Agriculture.” *2019 International Conference on Computer, Control, Informatics and its Applications: Emerging Trends in Big Data and Artificial Intelligence, IC3INA 2019*: 9–13.

Mennan, Husrev, Khawar Jabran, Bernard H. Zandstra, and Firat Pala. 2020. “Non-Chemical Weed Management in Vegetables by Using Cover Crops: A Review.” *Agronomy 2020, Vol. 10, Page 257* 10(2): 257. https://www.mdpi.com/2073-4395/10/2/257/htm (July 24, 2021).

Noon, Serosh Karim, Muhammad Amjad, Muhammad Ali Qureshi, and Abdul Mannan. 2020. “Use of Deep Learning Techniques for Identification of Plant Leaf Stresses: A Review.” *Sustainable Computing: Informatics and Systems* 28: 100443.

Ofori, Martinson, and Omar El-Gayar. 2020. “Towards Deep Learning for Weed Detection: Deep Convolutional Neural Network Architectures for Plant Seedling Classification.” *Faculty Research & Publications*. https://scholar.dsu.edu/bispapers/219 (July 24, 2021).

Patidar, Sanjay, Utkarsh Singh, Sumit Kumar Sharma, and Himanshu. 2020. “Weed Seedling Detection Using Mask Regional Convolutional Neural Network.” *Proceedings of the International Conference on Electronics and Sustainable Communication Systems, ICESC 2020*: 311–16.

Pattanayak, Santanu. 2017. “Pro Deep Learning with TensorFlow.” *Pro Deep Learning with TensorFlow*.

Qassim, Hussam, Abhishek Verma, and David Feinzimer. 2018. “Compressed Residual-VGG16 CNN Model for Big Data Places Image Recognition.” *2018 IEEE 8th Annual Computing and Communication Workshop and Conference, CCWC 2018* 2018-Janua: 169–75.

Sandler, Mark et al. 2018. “MobileNetV2: Inverted Residuals and Linear Bottlenecks.” : 4510–20.

Singh, Vijay et al. 2020. “Unmanned Aircraft Systems for Precision Weed Detection and Management: Prospects and Challenges.” *Advances in Agronomy* 159: 93–134.

Vypirailenko, Dmitrii, Elizaveta Kiseleva, Dmitrii Shadrin, and Mariia Pukalchik. 2021. “Deep Learning Techniques for Enhancement of Weeds Growth Classification.” *2021 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*: 1–6. https://ieeexplore.ieee.org/document/9459976/ (July 24, 2021).

Waheed, Abdul et al. 2020. “An Optimized Dense Convolutional Neural Network

Model for Disease Recognition and Classification in Corn Leaf." *Computers and Electronics in Agriculture* 175: 105456.

Wang, Zijie J. et al. 2021. "CNN Explainer: Learning Convolutional Neural Networks with Interactive Visualization." *IEEE Transactions on Visualization and Computer Graphics* 27(2): 1396–1406.

WangShui-Hua, and ZhangYu-Dong. 2020. "DenseNet-201-Based Deep Neural Network with Composite Learning Factor and Precomputation for Multiple Sclerosis Classification." *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)* 16(2s). https://dl.acm.org/doi/abs/10.1145/3341095 (July 23, 2021).

Yu, Jialin, Shaun M. Sharpe, Arnold W. Schumann, and Nathan S. Boyd. 2019. "Deep Learning for Image-Based Weed Detection in Turfgrass." *European Journal of Agronomy* 104: 78–84.

Zhang, Xian-Da. 2020. "Machine Learning." *A Matrix Algebra Approach to Artificial Intelligence*: 223–440. https://link.springer.com/chapter/10.1007/978-981-15-2770-8_6 (September 14, 2021).

Zhang, Zijun. 2019. "Improved Adam Optimizer for Deep Neural Networks." *2018 IEEE/ACM 26th International Symposium on Quality of Service, IWQoS 2018*.

Zhuang, Fuzhen et al. 2021. "A Comprehensive Survey on Transfer Learning." *Proceedings of the IEEE* 109(1): 43–76.

Ziska, Lewis H. "Climate Change and Agriculture: Promoting Practical and Profitable Responses Climate Change Impacts on Weeds."

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