ANALYSIS AND DETECTION OF CROP AND WEED CLASSIFICATION USING DEEP LEARNING IN PRECISION AGRICULTURE

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Analysis and Detection of Crop and Weed Classification Using Deep Learning in Precision Agriculture

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ABSTRACT

Precision agriculture is now an important tool for smart and automated farming that can increase agricultural productivity. Weed infestation is one of the many problems in agriculture which needs attention, as it not only impacts on the growth of crops, but also lowers the crop quality and the use of chemical herbicides. The old methods of weed control involve heavy labour, a long time and are not efficient in large field. Thus, the need for automated crop and weed classification systems based on Artificial Intelligence (AI) and Deep Learning (DL) has grown to be crucial in sustainable and smart farming applications.

This research compares several Convolutional Neural Network (CNN) based deep learning architectures for classification of wheat crop and weeds in real agricultural field. The collected self-generated data set comprised 2,190 RGB images of wheat crops and weeds obtained from agricultural fields located at Haryana, India, was used for training and evaluation. This study compares the performance of different deep learning models such as InceptionV3, U-Net, GoogleNet, VGG19, Xception, ResNet50V2, EfficientNetB0, MobileNetV2, VGG16 and DenseNet121. To enhance the generalization of the model and prevent overfitting, image resizing, normalization, and data augmentation (rotation, flipping, and zooming) were applied to the dataset.

The proposed architecture compares the various models based on various performance metrics such as accuracy, precision, recall, and f1 score to determine the most effective architecture for intelligent weed detection. Experimental results showed that the Xception model outperformed all models with accuracy of 85%, precision of 86%, recall of 83%, and F1-score of 84%. The main reasons for the superior performance of Xception are its efficient depthwise separable convolution mechanism and its robust feature extraction capability, which allowed to discriminate between similar-looking crop and weed patterns under complex agricultural conditions with high accuracy. Stable and competitive classification performance was observed for DenseNet121, MobileNetV2 and VGG19 while ResNet50V2 and VGG16 had comparatively poor performance because of their inability to process the changes in the field, illumination and overlapping vegetation pattern.

The findings of this research can be helpful in utilizing advanced CNN architecture for crop and weed classification and recognition. The developed framework can help in designing intelligent weed detection systems that can be integrated with drones and automated farming to improve efficiency of farming practices. Besides, this research also contributes in reducing the use of chemical fertilizers and human labor by promoting sustainable farming techniques.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AUC	Area Under Curve
CNN	Convolutional Neural Network
DL	Deep Learning
ML	Machine Learning
FCN	Fully Convolutional Network
FN	False Negative
FP	False Positive
GA	Genetic Algorithm
IoT	Internet of Things
IoU	Intersection over Union
k-NN	k-Nearest Neighbor
KL	Kullback–Leibler
LiDAR	Light Detection and Ranging
LBP	Local Binary Pattern
mAP	Mean Average Precision
MAV	Micro Aerial Vehicle
RGB	Red Green Blue
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
SSWM	Site-Specific Weed Management
UAV	Unmanned Aerial Vehicle
ReLU	Rectified Linear Unit
YOLO	You Only Look Once
VGG	Visual Geometry Group
FGOD	Fine-Grained Object Detection
NSPM	Neighborhood Similarity Pattern Module
PAM-FOG Net	Position Attention Mechanism – Feature Optimization Guidance Network

Chapter 1

INTRODUCTION

1.1 Precision Agriculture

One of the biggest problems with contemporary farming systems as a whole, and especially with crops like wheat, is how to manage weeds since they eat away at the crop's resources, including sunshine, nutrients, and water [1, 2]. The existence of weeds in the fields may lead to extreme degradation of crop production, high cost of production and environmental issues because of the extensive use of chemical herbicides [3, 4]. On a big scale, traditional weeding techniques like hand weeding and popular chemical herbicides are very labour-intensive, time-consuming, and ineffectual [5].

Triticum aestivum, also known as wheat, is a staple crop of immense importance all over the world, constituting a significant source of food and nutrition. It has a homogenous leaf arrangement and growth pattern that can be interrupted with the occurrence of weeds. The weeds are also unwanted plants that lower the total crop yield and quality on top of competing with wheat on the resources available like the sun, water and nutrients. The majority of the weeds like the Phalaris minor, Chenopodium album, Avena fatua can be confused with wheat when they are still small and that is the reason why they can hardly be identified by visual means. As Figure 1.1 and Figure 1.2 demonstrate, wheat and weed are also likely to have a similar shape, color, and texture. This similarity is a challenge to the traditional detection methods and it is the reason why methods based on CNN are applied. It is also important to note that the proper image recognition will be an important factor in ensuring that the right amount of herbicides is transported and that the damage to crops is minimized, thus, smart weed detection will be the crucial aspect of sustainable agriculture.

The major breakthroughs in the field of AI and computer vision have enabled the creation of fully automated systems of weed detector using deep-learning techniques. CNN has already demonstrated its power in image-based classification tasks and, therefore, has become significant in precision agriculture tasks [6, 7]. CNN has the

Figure 1.1: Sample images illustrating healthy wheat plants in field conditions

Figure 1.2: Representative images of weeds commonly occurring in wheat crops

capacity to differentiate weeds and crops using high-resolution images and enables specific weeds management practices that use less herbicides in environmentally friendly farming activities [8]. Despite the encouraging results of DL in detecting weeds, there are several obstacles. The visual properties such as color, shape, and texture are the same in weeds and crops and thus the classification becomes a complex task. In addition, the differences in the environment, light, and the type of soil can affect the work of the models [9]. There are a number of models available today and, even though they are effective in the laboratory, they cannot be extrapolated to different agricultural conditions. Some of the DL models that have been experimented with to classify weeds include InceptionV3, VGG19, U-Net, GoogleNet, and Xception. All the models have different trade offs in terms of accuracy, cost of calculation, and generalization. No long-scale studies comparing these models on the classification of weeds in wheat crops and optimization of the most successful architecture are made. This research will address the shortcomings of the weed identification in the present day.

1.2 Artificial Intelligence in Agriculture

AI is revolutionizing agriculture, offering intelligent automation, real-time monitoring, and precision-based decision-making. AI is the ability of computers to mimic human intelligence to carry out tasks that involve prediction, pattern recognition, image analysis, reasoning and learning. AI has revolutionized agriculture by introducing

new AI techniques like DL and computer vision.With the rapid evolution of AI techniques, especially DL and computer vision, traditional farming practices have been revolutionized into data-driven and automated operations. The application of AI technologies in crop monitoring, disease identification, yield prediction, irrigation management, pest identification and weed classification has become widespread in modern agriculture to enhance productivity and sustainability.

Weed invasion is one of the significant issues in the agriculture sector and it is a problem that can occur at any point during the crop growth, where it deprives crops of space, water, nutrients and sunlight. Conventional weeding practices (blanket herbicide application and manual weeding) are labour intensive, expensive and environmentally destructive. To overcome these problems, precision agriculture systems using AI have been developed for automatic crop and weed identification based on image processing and machine vision techniques. In recent years, the use of machine learning (ML) and deep learning has allowed intelligent systems to classify crops and weeds with high accuracy in complex conditions of agriculture.In the last years, ML and DL have been used to achieve accurate crop/weed classification in complex agriculture field environment [10, 11].

Deep Learning, a highly successful field of AI, has shown great success in agricultural image analysis due to its ability to automatically learn hierarchical and discriminative features from large-scale image datasets. CNNs, especially, have proven to be highly efficient in crop and weed classification because of their excellent feature extraction and pattern recognition capabilities. CNN-based methods do not require manual feature engineering and are able to handle RGB, hyperspectral and multimodal agriculture images to accurately classify them in a time efficient way [12, 13]. In recent years, AI models like YOLO, U-Net, Vision Transformers, Faster R-CNN, and Swin Transformers have been employed in precision agriculture to enable real-time weed detection and monitoring of crop growth.

There are recent studies that have indicated the success of AI-based systems to detect weeds in agricultural settings. Li et al. suggested the deep learning method for weed detection of winter wheat based on YOLOv8 and DINO architectures and verified that the method could be used for the detection of various weed species in complex fields with high accuracy [12]. To address the occlusion and complicated background, Xu et al. proposed a multimodal and multi-view deep learning framework based on Swin Transformer networks for weed detection in wheat fields, which achieved a higher identification accuracy [14]. In a similar fashion, Sulzbach et al. fine-tuned the YOLOv8 architectures for real-time weed detection in soybean crops and found that the architectures were efficient with less computational complexity [15]. To identify weeds

in real-time for precision herbicide application, Tetila et al. used UAV image acquisition and YOLOv5 models to detect soybean weeds in soybean fields [16]. Moreover, Niu et al. presented an intelligent weed recognition system for autonomous weeding robots based on a lightweight model called YOLOv8-ECFS for soybean field, which achieved high accuracy and real-time recognition efficiency.In addition, the model YOLOv8-ECFS for intelligent weed recognition in soybean field was presented by Niu et al. which has been proved as a lightweight model with high accuracy and real-time efficiency.

In addition, AI-driven ag systems are also being integrated with other high-tech technologies like drones, the Internet of Things (IoT), robotics, and autonomous vehicles to support intelligent agriculture. The UAV-based imaging system can quickly collect field data for large scale areas, and deep learning models can recognize the acquired images and accurately localize weeds and assess the condition of the crops. Data captured by the UAV imaging systems in the field can be analyzed very fast and the data in the system can be used for analyzing crop health conditions and also localize weed location using deep learning algorithms. Also, in the case of sustainable agriculture, robotic weeding and spraying with the help of AI technology helps to efficiently use herbicides and prevent environmental pollution [13, 17].

AI-powered agricultural systems have come a long way, but there are still challenges that need to be addressed, such as the lack of data, different growing environments, weed-crop similarity, computation complexity, and deployment constraints in real-time applications. However, ongoing advancements in deep learning architectures, transformer models, multimodal data integration, and lightweight neural networks stand to further enhance the efficacy and usability of intelligent weed management systems in precision agriculture. So, AI is becoming a key part of the smart farming technologies that aim to improve crop productivity, reduce manual labour and to make agriculture more sustainable.

1.3 Machine Learning and Deep Learning Techniques

For precision agriculture, ML and DL have appeared to be indispensable technologies in automating monitoring and decision-making tasks in agriculture. ML is a subcategory of AI in which a machine learns from data to make predictions with no need for explicit programming. The agricultural applications of ML cover topics such as crop classification, disease prediction, estimating yield, irrigation management, and weed detection. Most of the traditional ML techniques are based on manually extracted crop and weed features like color, texture, shape, and spectral characteristics [10, 11]. Some

of the most widely used ML algorithms are: Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees, and Random Forest classifiers.

Though classical ML algorithms are proven efficient, they suffer from several limitations. Feature engineering takes much time and expertise. In addition, classical ML algorithms are not efficient in solving real-world cases because of changing lighting conditions, non-homogeneous vegetation overlapping objects, hidden vegetation, and different growth stages of weeds [12]. Such issues can be handled by means of using Deep Learning, which outperforms traditional ML algorithms in solving agricultural image analysis tasks.

DL is an advanced subset of ML, which makes use of neural network architecture with multiple layers for extracting higher-level features automatically. Unlike traditionalML models, DL models can be trained without hand-crafting features and are more effective at image classification, image segmentation, and object detection tasks. In fact, CNNs have been the most popular deep learning architectures in agriculture applications, especially because of their ability to process high-dimensional image data and powerful features extraction capability [13, 14].

DL methods have been found to work effectively in weed detection and crop classification in the last few years. Li et al. applied YOLOv8 and DINO deep learning models in detecting the weeds for the winter wheat plantations in the field with high accuracy [12]. Similarly, Xu et al. developed a dual-path Swin Transformer model and multimodal image fusion technique for enhancing the efficiency and accuracy of the wheat weed detection system in the presence of leaf occlusions [14]. Also, Sulzbach et al. have fine-tuned YOLOv8 architectures in order to detect weeds in soybean plantations by reducing the computational complexity without affecting the detection accuracy significantly [15]. From the above findings, it is evident that the DL technology can be used to address the shortcomings associated with the ML approach.

These DL algorithms are highly useful for implementing real-time applications due to the use of UAVs, autonomous robots, and IoT-based smart farming systems. They can efficiently deal with massive agricultural image datasets and learn features automatically without any intervention from humans. This makes them suitable for automated crop monitoring and weed detection. Consequently, ML and DL techniques are very important in precision agriculture.

1.4 Fundamentals of Convolutional Neural Networks (CNNs)

CNNs represent a particular kind of DL networks that were created primarily to deal with image-processing and computer vision related tasks. Indeed, CNNs have shown

impressive performance in the sphere of agriculture imagery analysis with respect to such tasks as classification of crops, detecting weeds, recognizing diseases, calculating the yield, etc. This is attributed to the fact that CNN can extract automatically spatial and texture-related features from imagery. As compared to classical approaches based on ML techniques, CNNs do not require manually crafted features, but rather derive hierarchies directly from images [13, 15].

CNN architecture includes several layers, namely, convolutional layer, activation layer, pooling layer, fully connected layer, and an output layer. The crucial component of any CNN model represents the convolutional layer which is the part of the network dealing with the extraction of important visual information such as edges, textures, shapes, patterns, etc. This information is obtained by sliding filters or kernels across images.

Activation function such as ReLU is applied after convolution to make sure that the network has a non-linear transformation because this process is necessary for training complex patterns. In the following step, the size of the feature maps is made smaller to reduce the computational complexity while preserving the necessary information. This can be achieved through pooling layers.

High-level features that are obtained from the previous processes are passed to the fully connected layers, and the network is used to classify depending on the extracted features. In the end, the softmax activation function is used at the output layer in order to obtain the probability of every class including crops and weeds.

Many sophisticated CNN architecture models have been proposed in agriculture including VGGNet, ResNet, DenseNet, InceptionNet, Xception and MobileNet [12, 15, 17]. They differ in their depth, computation complexity, feature extraction capacity, and speed. Xception is known to include depthwise separable convolution for enhanced computational efficiency, and DenseNet implements dense connectivity between layers for improved feature passing.

The effectiveness of using CNN architecture models in the field of agricultural studies, especially for weed detection purposes, has already been shown. In an attempt to develop a precise yet lightweight algorithm that runs efficiently in real time, the authors of the study developed the YOLOv8-ECFS model [17]. In this work, the proposed architecture proved to perform well on detecting and classifying the weeds of soybeans. In another study, the YOLOv5 series were tested in soybean plantations by acquiring images via UAV technology to detect weeds in real-time settings [16].

1.5 Role of Image Classification in Precision Agriculture

The classification of images plays an important role in precision agriculture, allowing for automated analysis of images of agricultural fields for intelligent decision making and crop management. The use of AI, machine vision, drones, sensors and robotics are all part of the precision agriculture agenda to make farming more efficient. In the field of crop monitoring, weed detection, disease detection, irrigation management and yield prediction, image classification is one of the most important applications of computer vision among these technologies.

Agricultural image classification is the process of analyzing digital images captured from cameras, UAVs, satellite or sensor to detect specific pattern or objects like crop, weeds, pests, diseased plants, etc. Modern methods of agriculture monitoring require a lot of time, labor, and are often inaccurate in large-scale agricultural fields. Agricultural analysis in real-time is facilitated by automated image classification systems which are faster, more accurate and less expensive than human vision systems [11, 16].

Currently, image classification for weed detection is one of the most important applications of precision agriculture. Weeds are a problem to crops because they eat the same nutrients, need the same sunlight, water and space, and often reduce the yield and cause economic loss. Weed identification is crucial to help guide SSWM, which targets herbicides to the areas of a field that are infested with weeds instead of applying them over the entire area. This helps to decrease the amount of chemicals used, pollution in the environment and operating expenses [12, 14]. Occlusion, changing illumination, and morphological similarities of crops and weeds in the field are challenging for image classification systems, but AI-based systems can handle these quite well.

The use of DL-based image classification models has also greatly enhanced the precision agriculture system. CNN-based architectures are able to learn key visual image features automatically from agricultural images, and to accurately recognize their crop and weed classes. Weed detection and localization is further enhanced by advanced models for object detection like YOLO, Faster R-CNN, and Vision Transformers that enable the ability to perform real-time detection and localization of weeds [13, 15].

The research shows the increasing relevance of image classification in Agricultural Automation. Tetila et al. employed the RGB image acquisition system using the UAV platform and worked with models of YOLOv5 to detect weed species in real time in soybean crops in order to achieve precise herbicide application [16]. Likewise, Xu et al. used multimodal and multi-view image fusion methods for precise detection of weeds in wheat field in complicated environment [14]. Kong et al. suggested a lightweight segmentation network for cabbage weed detection and attained high precision in the

process of weed detection with low computation complexity [10]. The outcomes of the researches mentioned above show how effectively the use of image classification techniques can increase agricultural production and ensure its sustainability.

Therefore, image classification has become an integral component of modern technologies for precision agriculture aimed at crop monitoring, weed control, herbicide usage minimization and automated decision making on sustainable agriculture.

1.6 Overview of CNN Architectures Used in the Study

In the field of agriculture, DL architectures make a great contribution to the development of precision agriculture in that they ensure reliable performance of image classification, object detection and semantic segmentation in the agricultural environment. The capabilities of each of the CNN architecture in terms of feature extraction, computational speed and real-time execution differ. Therefore, the choice of the suitable architecture is essential in building a high-quality crop-weed classification system.

The comparative performance of various DL architectures used in crop and weed classification included: EfficientNetB0, InceptionV3, U-Net, MobileNetV2, GoogleNet, VGG19, Xception, ResNet50V2, VGG16 and DenseNet121. These were selected on account of their proven efficacy in computer vision tasks, as well as agriculture image analysis tasks.

Networks like GoogleNet and InceptionV3 use multi-scale convolutions to gather multi-scale spatial information at multiple resolutions while maintaining computational efficiency. These models have shown to be effective in an agricultural classification application with different weed shapes and field conditions [18, 19]. The architectures based on VGG are characterized by deep sequential convolution layers, whereby VGG16 and VGG19 are popular choices used for their ability to extract features and gain a higher level of classification accuracy. Previously published works showed that VGG-based models performed well at weed detection tasks with high F1-scores and recall values because of its ability to learn good representation of the input image [20].

U-Net is an image segmentation network with skip connections and an 'encoder-decoder' structure, which is commonly used in agricultural image segmentation. In dense vegetation, the U-Net-based models have achieved outstanding performance in the crop segmentation and weed segmentation at the pixel level [21]. Xception, in turn, uses depthwise separable convolutions to gain computational efficiency with high classification accuracy. Due to the light-weight structure of Xception, it can be trained quickly and has good generalization ability in complex agricultural environments [22].

In recent years, the research has also turned to lightweight architectures like

MobileNetV2 and EfficientNetB0 for real-time weed detection systems to be used in embedded devices and agricultural robots. These lightweight networks compress the model parameters and computation, but achieve high detection performance [23, 24]. DenseNet121 has dense connectivity between its layers, allowing for more efficient feature propagation and reuse, resulting in more effective backpropagation and avoiding information loss. ResNet50V2 is a recently developed model that solves the problem of vanishing gradients and facilitates the development of more complex deep networks for images.

There are also some remarkable progress in modern object detection architectures like YOLOv5, YOLOv8, SegFormer, Swin Transformer, and transformer-based semantic segmentation networks, which have achieved great accuracy for applications in precision agriculture [18, 19, 25]. They offer real time, high-speed weed detection and localization in different field environments. The incorporation of attention mechanisms, lightweight feature extraction units, and transformer structure has greatly enhanced the accuracy of weed classification and computational efficiency.

For this reason, multiple CNN architectures were compared to gain insights into the advantages and disadvantages of the various CNN models used for crop and weed classification in precision agriculture.

1.7 Need for Automated Weed Detection Systems

Weed infestation is one of the biggest problems faced in agricultural production globally. Weeds eliminate essential resources to crops (nutrients, water, sunlight, and space) which cause yield and quality losses. Uncontrolled weed growth can cause major losses in agricultural production and economic losses to farmers for crops like wheat, maize, soybean and cotton [19, 24]. Current methods of weed control are mainly based on manual work and the use of broad-spectrum herbicides, whose application is not efficient, cost effective and environment friendly.

This manual methods of weed removal are labor-intensive, time-consuming and impractical for large-scale agriculture. Moreover, improper use of herbicides results in pollution of the environment, degradation of soil and resistance to the herbicide, as well as detrimental effects on human health [25]. Therefore, there is a great demand for the intelligent and automated system of weed management, deriving from the concern of sustainable agriculture and ecological conservation.

AI, computer vision and DL-based automated weed detection systems can effectively address these issues. The use of cameras, drones, sensors, and DL algorithms allows them to automatically detect and locate weeds with remarkable accuracy in agricultural

areas. SSWM is a management strategy that uses automated weed detection to apply herbicides to only areas of the field that are infested with weeds, not across the whole field [24]. This substantially reduces the use of chemicals, the impact on the environment and the operational cost.

In recent years, significant progress has been made in DL, leading to more accurate and efficient weed detection systems. CNN-based architectures can automatically extract the spatial, texture and morphological features from agricultural images without the need of manually extracted features. In the field environment with complex scenes, the real-time performance is further enhanced using transformer based architectures and lightweight object detection models.In the field environment with complex scenes, transformer based architectures and lightweight object detection models further enhance the real-time performance. Research on weed detection has shown that the YOLOv8 model, SegFormer model, Swin Transformer model, and Lightweight CNN model have achieved excellent accuracy and recall performance for weed detection under different lighting conditions, different occlusion situations, and heavy vegetation environments [19, 21, 22].

Drone-based weed detection systems are also becoming important in precision agriculture. Aerial images captured by UAVs and DL models can be used for large-scale field monitoring and the mapping of weeds with great speed and precision [24]. These systems aid farmers in making timely decisions on weed management and optimize herbicide systems. Likewise, lightweight DL models for edge devices and agricultural robots enable autonomous farming systems to process data in real-time for robots on the farm [23, 20].

Another significant benefit of an automated weed detection system is that they can contribute to sustainable and smart agriculture practices. Intelligent weed management systems help to reduce dependence on herbicides, enhance crop productivity, reduce labour and reduce damage to the environment. In addition, the potential for the integration of AI, IoT, robotics and autonomous vehicles is anticipated to further expand the precision agriculture systems' capabilities in the future.

As a result, automated weed detection systems are recognized as an indispensable tool in contemporary precision agriculture, delivering effective, precise, and eco-friendly solutions in intelligent crop management and weed control.

1.8 Research Objectives

1. A scientific comparison of the popular CNN structures, including InceptionV3, U-Net, GoogleNet, VGG19, and Xception, to detect weeds in wheat fields.

2. The key evaluation metrics of the model performance are used to compare the performances of various models to determine the most appropriate architecture to apply to the crop- weed classification problems.

3. To facilitate precision agriculture and enhance field-level decision-making, the feasibility of these DL models in real time and autonomous weed detection systems is under consideration.

1.9 Overview of the Study

The remaining paper will be structured in the following way. Chapter 2 conducts a review of the available literature on the topic of weed detection and crop-weed classification with the help of DL and computer vision methods. Chapter 3 covers the methodology used in the current work, comprising data set preparation, pre-processing, model structure, and training. In chapter 4 , the experimental findings of the comparative analysis of the chosen CNN models are provided and discussed. Lastly, chapter 5 will bring the paper to an end by summarizing the main findings and provide possible directions of future researches.

Chapter 2

LITERATURE SURVEY

The initial research on the detection of weeds mainly used conventional machine learning and computer vision methods that employed handcrafted features, including color, texture, and spectral features. Naveed et al. suggested a saliency-based weed detection model based on UAV multi spectral imagery and a predictive coding neural network, which produced saliency maps to separate crops and weeds and obtained 94.38 percent accuracy at the cost of minimum computation [26]. Likewise, Raja et al. proposed a spectral fluorescence imaging system to control weeds in a celery field by robots, where crop signaling was done with a Rhodamine-B, to be able to distinguish between crops and weeds, with almost 100 percent detection accuracy in the dense field [27]. Though these methods showed encouraging outcomes, they are limited by the reliance on human-made characteristics and controlled imaging conditions to be scalable and applicable to various agricultural settings.

The latest developments in DL have contributed to the enhancement of the performance of the weed detector greatly, as it allows to extract the features that are not to be identified manually by the user. Lottes et al. introduced a completely convolutional network (FCN) that uses sequential information of the image as pixels and performs pixel-wise segmentation of the crop– weed, which showed robust generalization in changing field conditions [28]. Tetila et al. compared several DL object detection models, such as Faster R-CNN and YOLOv3, to the WEED6C dataset (almost 10,000 annotated samples) and found that Faster R-CNN performed better on the task of object detection in terms of recall and F1-score [29]. Moazzam et al. proposed a patch-image classification system with an adapted VGG-based CNN (VGG-Beet) to detect weeds in sugar beet fields, with a higher classification strength than semantic segmentation networks like U-Net and DeepLab [30]. Moreover, Mulay et al. explored ensemble DL approaches involving CNN, VGG16, and ResNet50 networks and demonstrated that ensemble strategies like stacking and majority voting enhance crop–weed classification accuracy [31].

Subsequent studies have been done on real-time detection systems based on the latest object detection architectures. Sun et al. have created a machine-vision system based on the YOLOv8 and YOLOv9 models trained on field images of various locations and multiple crop types, with maximum mean average precision (mAP50) of 86.2% in multi-species weed detection [32]. Likewise, Upadhyay et al. trained lightweight YOLO models on images (4,828 annotated images) to deploy them on edge devices, with a mAP of 0.83 at 0.5, and the ability to run in real-time [33]. Additional enhancements have been suggested including specialized architectures like FGOD-YOLOv8, that uses cross-scale feature fusion and attention modules to enhance the detection of small-objects [34] and YOLO-CWD, which uses hybrid attention mechanisms and a new loss function to enhance localization accuracy in crop-weed detection tasks [35]. WeedsDetectNet also incorporates green attention and adaptive feature fusion modules to improve the detection performance in agro-complex environments [36]. An overarching survey by Pai and colleagues emphasizes that current systems of weed detection are majorly based on DL architectures that are trained on large annotated datasets, but problems like dataset diversity, environmental variability, and computational efficiency pose a major challenge to real-life application [37]. Table 2.1 summarises the existing weed detection and classification techniques reviewed in this section.

Table 2.1: Summary of Existing Weed Detection and Classification Techniques

Authors	**Dataset**	**Model Used**	**Accuracy Level**
Inkyu Sa et al. (2018)	Sugar beet and weed dataset	SegNet (CNN-based dense semantic segmentation)	F1-score: ~0.8, AUC: 0.78
Xiaojun Jin, Jun Che, Yong Chen (2021)	1150 images (augmented to 11,500)	CenterNet + Genetic Algorithms (GA) for segmentation	Precision: 95.6%, Recall: 95.0%, F1-score: 0.953
Zulfadli Mawardi	*Chromolaena odorata* (Siam weed) dataset	Deep Learning Object Detection Model	Precision: 0.95, Recall: 0.82, F1-score: 0.88

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Table 2.1 – *Continued from previous page*

Authors	**Dataset**	**Model Used**	**Accuracy Level**
Shuangyu Xie, Chengsong Hu, Muthukumar Bagavathiannan, Dezhen Song	TAMU Nutsedge Dataset (Raw and Synthetic Data)	Mask R-CNN (Modified with KL-Divergence Loss and NSPM)	False Negative Rate: 0.4%
Philipp Lottes et al.	Sugar beet fields near Bonn and Stuttgart	Fully Convolutional Network (FCN) with Sequential Module	Crop Recall: 94%, Weed Recall: 91%
S. Imran Moazzam et al.	Agrocam Sugar Beet Dataset (Pakistan), Parrot Sequoia Dataset (Switzerland), Red Edge Dataset (Germany)	VGG-Beet CNN (Patch-based Classification)	Agrocam: 86.3%, Parrot Sequoia: 90.7%, Red Edge: 92.4%
Jiahua Bao et al.	Custom dataset collected from a small-scale farmland environment	PAM-FOG Net (Lightweight CNN-based model with feature optimization)	mAP@0.5:0.95 = 0.364, mAP@0.5 = 0.709
Zineb Laftouty et al.	Custom dataset from FPL Smart Farm	Deep learning models (CNN, SVM, LBP) for weed detection	Up to 100% accuracy for certain models
Hossein Chegini et al.	Synthetic dataset (Leaf-based, Plant-based, Mixed)	Mask R-CNN	mAP: 93%, Testing Accuracy: 95.3%

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Table 2.1 – *Continued from previous page*

Authors	Dataset	Model Used	Accuracy Level
Irshad Ahmad et al.	Dataset of 200 images per class	Haar Wavelet Transform (HWT) + k-Nearest Neighbor (k-NN)	94%

2.1 Evolution of Weed Detection and Deep Learning Architectures

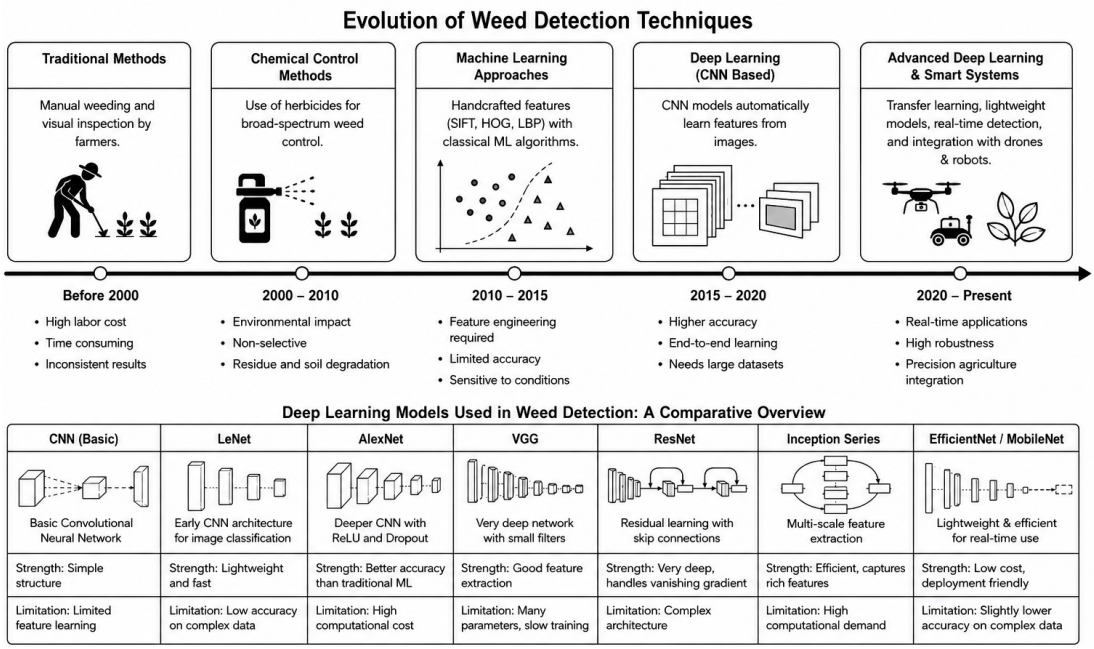

Figure 2.1: Evolution of Weed Detection Techniques and Deep Learning Models in Precision Agriculture

Figure 2.1 shows the progress of weed detection methods adopted in precision farming from manual to advanced DL AI based weed detection. Weed management was at first mainly done by hand and chemical herbicides spraying, which were environmental harmful, labour intensive and time consuming. As a result of development of ML methods, hand crafted feature extraction approaches like SIFT, HOG, and LBP were developed for weed classification, but these were not very accurate and had poor adaptability in complex agricultural environments.

The figure also emphasizes the importance of DL and CNN based methods, which demonstrated substantial enhancements in classification accuracy for crops and weeds, leveraging the automatic feature extraction and end-to-end learning capabilities. New

architectures like ResNet, InceptionNet, EfficientNet and MobileNet have contributed to the accuracy level of weed detection while minimizing the complexity of the computations and enhancing the real-time performance. In recent years, the integration of light weight CNN models, drones, robotic systems and precision agriculture technologies into automated and intelligent weed management systems are also showcased.

The bottom portion of the diagram gives a synopsis of the major CNN frameworks used for analyzing agricultural images, as well as the strengths and weaknesses of these structures. Basic CNN frameworks give rudimentary properties to learn from, while deep CNN frameworks such as VGG and ResNet enhance the classification capability by providing advanced feature extraction and residual learning functionality. EfficientNet and MobileNet are efficient frameworks that can be deployed in resource-constrained environments and for real-time applications.

Chapter 3

Methodology

3.1 Proposed Architectural

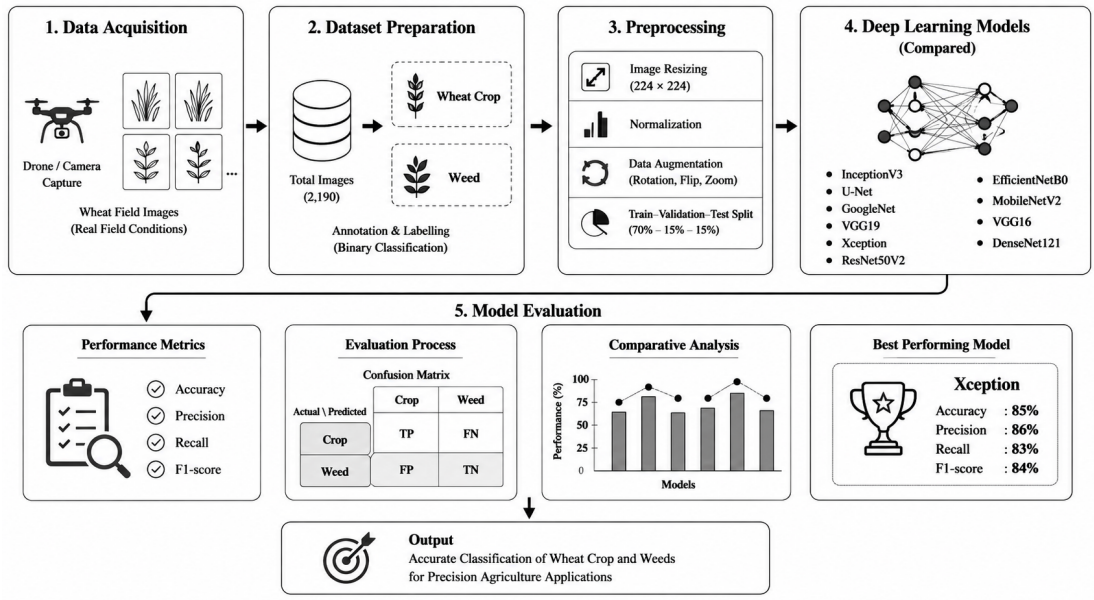

Figure 3.1: Proposed deep learning-based crop and weed classification system

Figure 3.1 shows the overall architecture of the proposed system for DL crop and weed classification system for precision agriculture applications. There are six major stages in the architecture, including data acquisition, dataset preparation, preprocessing, application of the DL model, prediction of output, and evaluation of the model. This workflow offers a systematic approach for automated crop and weed identification, with CNN-based architectures.

The first phase of the architecture is *Data Acquisition* in which the images of wheat fields are captured in a real field with mobile phone cameras and drone imaging systems. These images include wheat crops and several species of weeds, and were taken in a variety of environmental and lighting conditions. The field pictures obtained (collected) are the primary data set needed to train and assess the DL models. The second step

is called *Dataset Preparation*. In this, the gathered RGB images have been arranged and classified into two main groups: wheat crops and weeds. In this study, the dataset comprises 2190 RGB images with annotations. Supervised learning requires proper annotation and labeling, as these help the CNN models to learn discriminative features for each class.

The third stage corresponds to the *Preprocessing stage*. To ensure uniformity when feeding images into all DL architectures, all images are resized to a fixed size in the preprocessing step (224 X 224) pixels. The normalisation of the images follows to scale the pixel values and to stabilize the learning process. To boost data diversity and minimize overfitting, data augmentation strategies like rotation, flipping and zooming are applied and additional data is generated. The dataset is split into train, validation and test sets with a ratio of 70:15:15. The fourth stage is the implementation of several *Deep Learning Models*. Comparative analysis is performed on the several CNN architectures InceptionV3, U-Net, GoogleNet, VGG19, Xception, ResNet50V2, EfficientNetB0, MobileNetV2, VGG16, and DenseNet121. These architectures are trained separately to learn different types of features, such as spatial, texture, and structural features, from agricultural images for the correct classification of the crop and weeds in these images.

The main part of the architecture depicts the general *CNN workflow* applied to all models. The input image is first passed through convolutional layers to extract the features and then passed through pooling layers to reduce the dimensionality of the features and to achieve feature selection. High level feature learning and classification is then achieved by fully connected layers. Lastly, the output layer having softmax activation function predicts the last class label either wheat crop or weed. The last step is the *Model Evaluation* where the created models are tested on significant performance metrics like accuracy, precision, recall, and F1-score. The best architecture is also chosen by using confusion matrix analysis and comparative performance analysis. Experimental results also showed that the Xception model has shown better classification results, because it has the ability to extract features efficiently, as well as having balanced evaluation results.

Therefore, the architecture as illustrated in Figure. 3.1 is a comprehensive end-to-end solution for intelligent crop and weed classification in precision agriculture based on DL techniques.

3.2 Workflow

Figure 3.2 shows the pipeline for weed detection in precision agriculture. This will start with the image acquisition where the total images of 2,190 fields of wheat crops

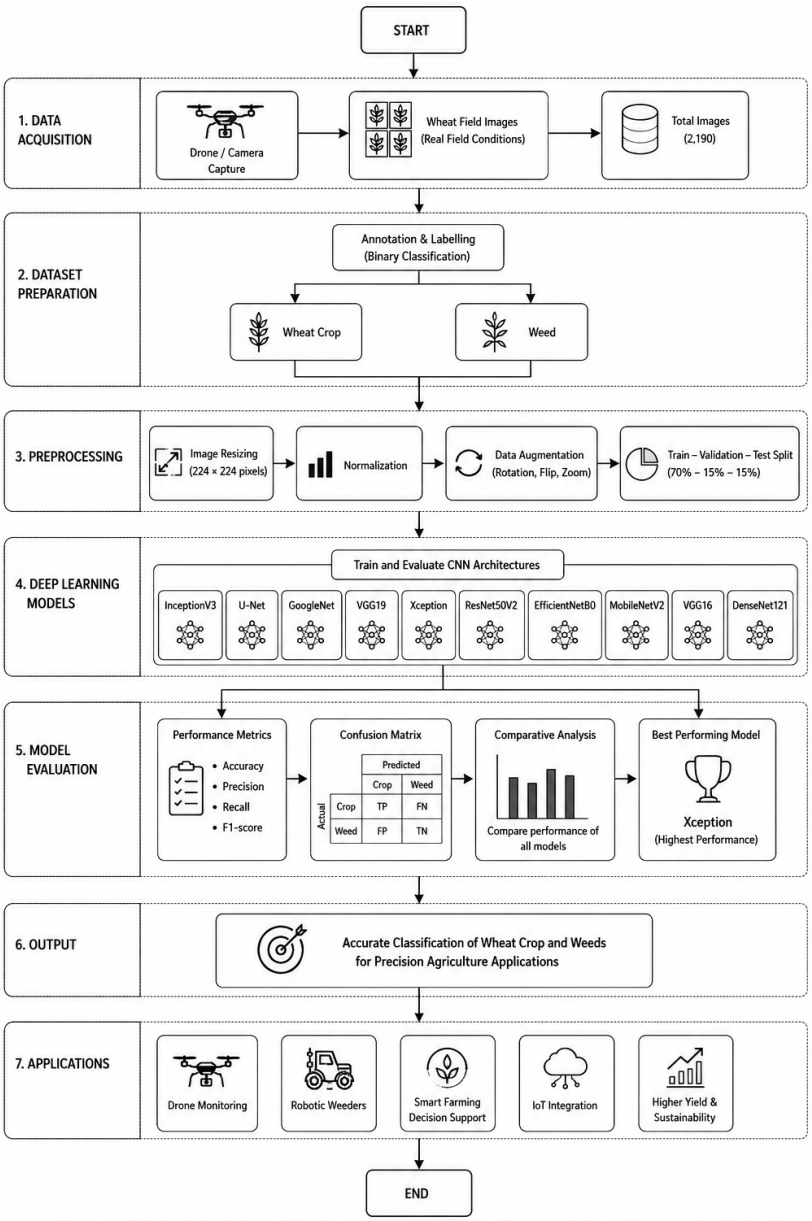

Figure 3.2: Proposed pipeline for weed detection in wheat fields

and weeds were acquired under varying conditions of lighting and environment. These pictures were later undergone data preprocessing, which involved normalization and resizing so as to have similar input dimensions. Moreover, data augmentation methods like rotation and flipping were used to enhance the variety of the data set, enhance generalization of the model and minimize overfitting in the training phase. After preprocessing, the data was separated into three parts training, test and validation to allow an accurate assessment of model performance. The images were properly annotated at this phase to ensure that crop and weed classes are well supervised during the learning phase. To carry out the comparative analysis, five popular DL architectures were chosen, including InceptionV3, U-Net, GoogleNet, VGG19, and Xception. The models were trained using relevant hyperparameter tuning to maximize the learning performance and classification. The evaluated trained models were then tested on conventional performance measures. The results were compared by tabular presentation and graphical illustration to bring out differences in the performance of the models. The overall performance of the experimental findings supported that Xception performed the best as it had the highest classification accuracy and balanced metric scores, which implies that it can generalize well to crop–weed discrimination. Lastly, interpretation of the most important findings and the identification of possible future research directions, including the expansion of the dataset and the use of more sophisticated ensemble or hybrid DL methods, are the final stages of the workflow. This end-to-end pipeline, as shown in Figure 3.2, refers to the effectiveness of CNN-based models to identify weeds in intelligent agricultural systems in automated and real-time.

3.3 CNN Architecture Used for Crop and Weed Classification

The Convolutional Neural Network (CNN) architecture used in this study is illustrated in Figure 3.3. CNN is one of the most widely used DL architectures for image classification tasks due to its powerful feature extraction and pattern recognition capabilities. In precision agriculture, CNN models are highly effective for crop and weed classification because they can automatically learn complex spatial and texture-based features from agricultural field images without requiring manual feature engineering.

From Figure 3.3, one can see that the structure of the CNN consists of taking input image data in the form of a 224×224×3 RGB image. Filters are used on the input image in various convolution layers in order to capture important aspects of the image, including edges, shape, textures, and patterns of the crops and weeds in the image. From the application of convolution operations, there is an output of the feature maps which have captured certain features from the input image.

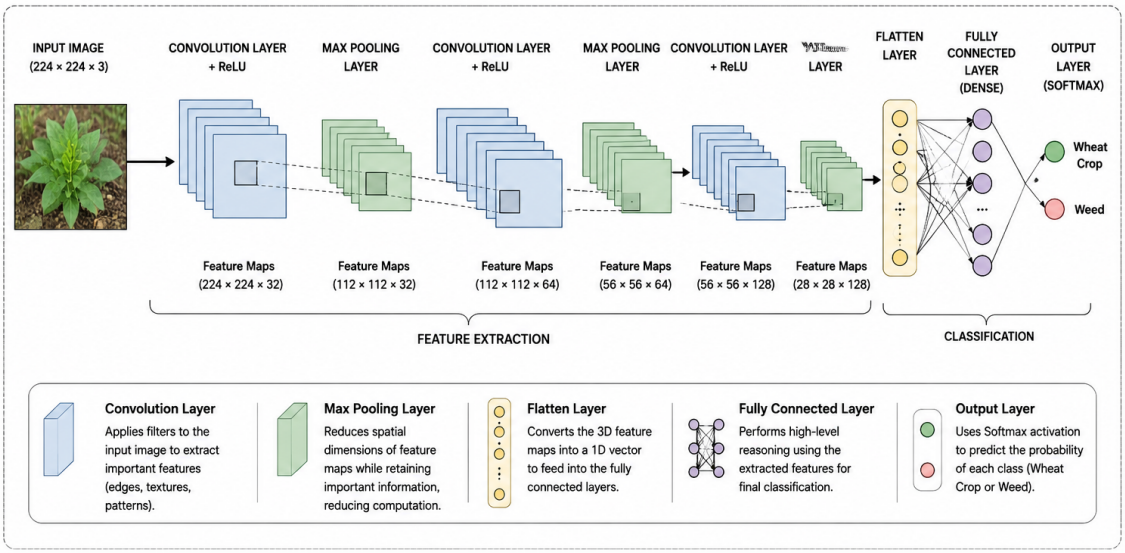

Figure 3.3: Architecture of Convolutional Neural Network (CNN) for Wheat Crop and Weed Classification

Following convolution, activation is performed using the ReLU to enable non-linearity in the CNN. After convolution and ReLU functions, max-pooling is used to reduce the dimensionality of the feature maps. This process helps in making the model robust towards variation in orientation and illumination in the images. Through successive use of convolution and pooling processes, the features of the image are better classified.

Subsequent to the learning of features using the CNN, the multi-dimensional feature maps are flattened into one dimension. Then, the features are fed to fully-connected dense layers where high-level reasoning and classification take place. Lastly, the probabilities assigned by the classifier using the Softmax activation function represent the likelihood of the input image being a part of either the wheat crop or the weeds category.

Figure 3.3 shows how the whole process of image classification through CNNs takes place in the current study to facilitate crop and weed detection in fields. The capacity of the architecture to learn hierarchical features makes CNNs suitable for precision agriculture problems like identifying crops and weeds amid complex environmental conditions such as varied illumination, overlapping plants, and visually indistinguishable weed species.

3.4 Dataset Description

The dataset, which was used in the study is 2,190 images, with 1,000 images depicting wheat crops and 1,190 images depicting the different species of weeds. These pictures were taken under actual agricultural field conditions in the state of Haryana in India with the help of mobile phone cameras. In particular, Xiaomi and OnePlus smartphones were used to gather the pictures, and this way, the dataset will represent a real-life field situation faced by farmers and agricultural specialists. The pictures have been geotagged and taken to the very field of wheat culture, thus maintaining the reality of the actual agricultural fields. Moreover, the pictures were taken with different lighting conditions, including the time of the day and weather changes that improve the strength and the realistic aspect of application of the data to DL-based classification processes. All the pictures in the data set are in the RGB format, and this enables the models to acquire fine-grained color-based features that are necessary in separating crops and visually similar species of weeds. The data has a number of weeds, which are prevalent in wheat production, i.e., Nutgrass, Burr Medic, Chickweed, and Toothed Dock. These weed species have been chosen because of their common occurrence in wheat fields and the magnitude of their effects on crop growth, yield decrease as well as the competition of basic requirements like nutrients, water, and sunlight.

Several techniques for data pre-processing and augmentation were employed to improve the performance of DL models. To maintain structural integrity and spatial data, all of the photos were downsized to the same size without altering the image aspect ratio. Also, several augmentation methods were used to purposefully augment the variability of the dataset and improve the generalisation of the model, such as image rotation, horizontal and vertical flips, brightness, and normalisation of contrasts. The pixel values have also been scaled to the range of 0-1 which is useful to stabilize the training process and convergence in the backpropagation process. The diverse environmental and biological variability (soil texture, lighting conditions, background complexity, and pattern of the weed distribution) is introduced into the dataset. This diversity guarantees that the trained DL models can be able to adapt to actual agricultural conditions as opposed to the controlled conditions found in laboratories. Therefore, the data can be used as a trustworthy and thorough basis of assessing and refining DL models that will be used to detect precision weeds and crop-weed in wheat farming systems.

Chapter 4

RESULT AND DISCUSSION

4.1 Model Evaluation Metrics

To quantify the performance of CNN-based models as far as the detection of weeds in precision agriculture is concerned, the following five DL models were trained and evaluated on a self-curated dataset of 2,190 images with both crop and weed-related examples in wheat fields, namely InceptionV3, U-Net, GoogleNet, VGG19, and Xception. In order to evaluate the performance of the aforementioned models, the following evaluation measures were used: accuracy, precision, recall, f1 score, and the confusion matrix analysis. The use of the confusion matrix and terms such as TP (true positives), TN (true negatives), FP (false positives), and FN (false negatives) gives us more insight into the performance of each model. These evaluation measures can give a thorough evaluation of the various aspects of model performance and reliability.

Precision: Precision represents the number of times the model makes accurate predictions of positive instances compared to the total predictions of positive instances, which means how accurately the model predicts positive samples with FP.

Recall: Recall is the rate of the number of real positive cases that the model correctly recognizes.

F1-score: F1-score is the harmonic mean of recall and precision, and is a balance score of the classification performance of a model.

Accuracy: Accuracy is the proportion of the instances correctly predicted to the total number of instances in the dataset.

4.1.1 Comparison of Precision Scores Across Deep Learning Models

Table 4.1: Precision Comparison of Deep Learning Models for Crop and Weed Classification

S.No	Model	Crop Precision	Weed Precision
1	InceptionV3	0.88	0.79
2	U-Net	0.82	0.80
3	GoogleNet	0.84	0.85
4	VGG19	0.97	0.90
5	Xception	0.93	0.97
6	ResNet50V2	0.76	0.80
7	EfficientNetB0	0.80	0.83
8	MobileNetV2	0.81	0.84
9	VGG16	0.77	0.81
10	DenseNet121	0.83	0.86

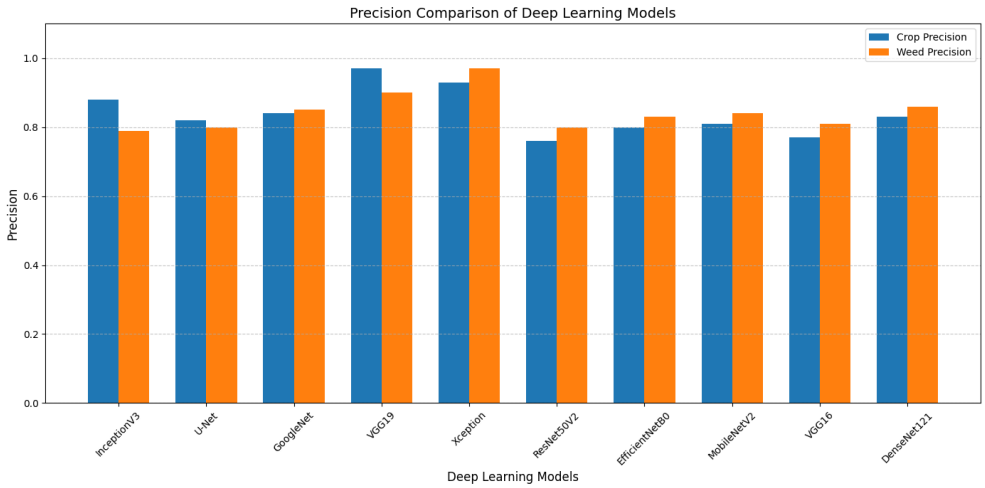

Figure 4.1: Comparison of precision scores across models for crop and weed classification.

Table 4.1 and Figure 4.1 show the accuracy comparison among various DL models for crop and weed classification, respectively. One of the most important assessment criteria in agricultural image classification is precision, which relates to the ability of a model to classify a crop or weed and to avoid making false predictions. For precision based weed detection systems, high precision values are important so that herbicide is not applied incorrectly and crop management is efficient.

The overall performance of the Xception model, as presented in table 4.1 and figure 4.1, is the best of all the models evaluated. It achieved a precision value of 0.93 for crops and 0.97 for weed, the best weed precision of all the architectures tested. The high performance of Xception is the result of its depthwise separable convolution mechanism that is more efficient in the extraction of features with lower computational cost. This architecture allows the model to recognize the spatial and texture details between the crops and weeds in the field, even when conditions are difficult in an agricultural field. The high weed precision also suggests that the model is suitable for both high precision and reliable classification of weeds for precision agriculture applications.

The precision for both crops and weeds with VGG19 was also very high, at 0.97 and 0.90, respectively. The crop precision of VGG19 was found to be the highest among all models, making it very effective to detect the crop features accurately. The deeper the architecture of VGG19, the more it is able to learn the hierarchical and discriminative features of agricultural images. Its weed precision was however slightly lower than that of Xception, indicating that Xception offers higher generalization and adaptability to different appearances of the weeds and environmental conditions.

GoogleNet, DenseNet121, MobileNetV2 and EfficientNetB0 had a fairly equal and steady performance. For a crop the precision for GoogleNet and DenseNet121 were 0.84 and 0.83, respectively, and for weeds their precision were 0.85 and 0.86, respectively. MobileNetV2 and EfficientNetB0 achieved a moderate precision score and satisfactory result. These models provide a good trade-off between computational cost and classification accuracy, making them good choices for lightweight agricultural systems, embedded devices and real time weed detection applications.

The values for precision for InceptionV3 and U-Net were acceptable, but lower than the other two. The precision values for both crops and weeds were 0.88 for InceptionV3 and 0.79 for U-Net. These models can be used to extract multi-scale image features, but they are not suitable to discriminate visually similar crop and weed patterns in complex crop field environment.

When comparing the overall performance of all the models evaluated, ResNet50V2 had the lowest performance, with a crop precision of 0.76 and a weed precision of 0.80. The same was observed regarding the precision values for crops (0.77) and weeds (0.81) for VGG16. This may be caused by the difficulty in extracting the highly discriminative agricultural features and dealing with the different illumination, occlusion and background complexities of field datasets in the reduced performance of these models. Smaller precisions mean that the probability of false classifications is larger and thus the reliability of weed management systems using automation may be reduced.

As seen in Table 4.1 and Figure 4.1, the advanced DL models like Xception and

VGG19 clearly outperform the traditional CNN models in the crop and weed precision classification problem, as these models are better at extracting and representing features.

4.1.2 Comparison of F1-score Across Deep Learning Models

Table 4.2: F1-Score Comparison of Deep Learning Models for Crop and Weed Classification

S.No	Model	Crop F1-score	Weed F1-score
1	InceptionV3	0.79	0.77
2	U-Net	0.81	0.82
3	GoogleNet	0.84	0.81
4	VGG19	0.84	0.89
5	Xception	0.90	0.94
6	ResNet50V2	0.75	0.77
7	EfficientNetB0	0.79	0.81
8	MobileNetV2	0.80	0.82
9	VGG16	0.76	0.78
10	DenseNet121	0.82	0.84

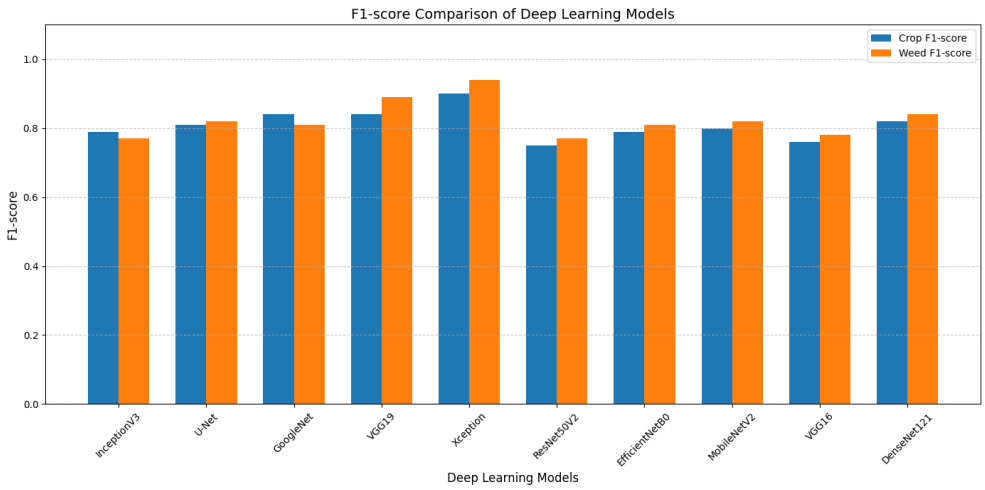

Figure 4.2: Comparison of F1-scores for crop and weed classification across models.

The comparative analysis of the F1-scores presented in Table 4.2 and illustrated in Figure 4.2 provides significant insights into the performance of different DL architectures

for crop and weed classification. In classification problems, the F1 score is a very significant evaluation metric, as it is the harmonic mean of the precision and recall. The F1 Score gives a fairer evaluation than just accuracy because it also takes into account FN and FP. In the field of agriculture, keeping the F1 score high is important to guarantee the success of the classification process in different environmental and agricultural conditions.

Table 4.2 shows that Xception was the best overall performance among all the evaluated models with a crop F1-score of 0.90 and a weed F1-score of 0.94. The key to the superior performance of Xception is its incorporation of depthwise separable convolutions that are very efficient at extracting features, but still have lower computational complexity. This method of architecture allows the model to better deceive a human into perceiving the texture, colour and spatial differences between crops and weeds as finer grained than traditional CNN models. The high weed F1-score also shows that the excellent balance maintained by Xception in relation to weeds makes it a desirable neural network because of reduced detection of false weeds and FN. All the characteristics discussed above explain why Xception is the best choice for precise agriculture and automated weed detection systems.

Also, VGG19 had impressive performance in relation to classification of images, having achieved an F1-score of 0.84 and 0.89 for crops and weeds, respectively. The ability of VGG19 to have a deep architecture helps it to attain a high level of complex hierarchy of image representation. As a result, the ability of the model to distinguish between visually similar objects increases significantly. Moreover, the model proved to be stable and reliable when performing classifications on crops and weeds. Nevertheless, VGG19 is very complicated and has several layers making it consume large amounts of processing power and memory space.

Moderate yet balanced performance was achieved for DenseNet121, GoogleNet, MobileNetV2 and U-net. F1-scores for DenseNet121 were 0.82 (crop) and 0.84 (weed), and for GoogleNet the scores were 0.84 (crop) and 0.81 (weed). These algorithms represent the right balance between fast performance and accurate classification. DenseNet121 uses densely connected layers to increase gradient propagation through its layers. In addition, MobileNetV2 had balanced results with fewer computational costs that made it perfect for using on devices-oriented networks such as IoT agriculture devices. Moreover, another strength of using U-net algorithm is the fact that it provides balanced performance which makes it perfect for segmentation-based agricultural applications with its unique encoder-decoder structure. However, it does not provide as good overall discriminative performance as Xception and VGG19.

The results of InceptionV3 and EfficientNetB0 were good, but they still faced some

challenges in complex agricultural field conditions. The F1-scores for both crops and weeds were 0.79 for InceptionV3 and 0.77 for EfficientNetB0. These architectures are efficient in extracting multi-scale features of the image, but can have problems when crops and weeds have very similar visual features, or when there is background noise and variation in illumination.

ResNet50V2 showed the lowest performance among all models evaluated with the F1-scores of 0.75 and 0.77 for crops and weeds, respectively. VGG16 also worked comparatively poorly with 0.76 for crops and 0.78 for weeds. These models are less effective perhaps because there is a lack of discrimination between features and adaptability to the very diverse agricultural landscapes. These models tend to have lower F1 scores, which means that they are more likely to miss detections (FN) or confuse the plants with weeds (FP), making them more challenging to use for automated weed detection.

In summary, it is evident from the results in Table 14.2 and Figure 4.2 that the advanced DL architectures which are able to extract features efficiently such as Xception and VGG19 are more effective than the conventional convolutional neural network architectures for the crop and weed classification problem. The high performance of their F1-score indicates high generalization, strong feature representation and high robustness for the practical precision agriculture applications.

4.1.3 Comparison of Recall Across Deep Learning Models

Table 4.3: Recall Comparison of Deep Learning Models for Crop and Weed Classification

S.No	Model	Crop Recall	Weed Recall
1	InceptionV3	0.74	0.79
2	U-Net	0.79	0.83
3	GoogleNet	0.84	0.85
4	VGG19	0.88	0.81
5	Xception	0.93	0.90
6	ResNet50V2	0.74	0.76
7	EfficientNetB0	0.78	0.80

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Table 4.3 – *Continued from previous page*

S.No	Model	Crop Recall	Weed Recall
8	MobileNetV2	0.79	0.81
9	VGG16	0.75	0.77
10	DenseNet121	0.81	0.83

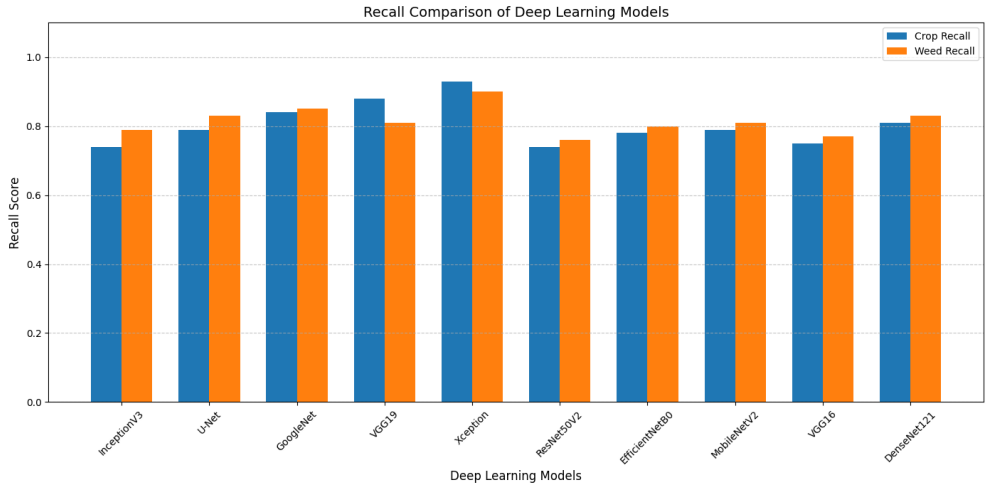

Figure 4.3: Comparison of recall scores for crop and weed classification across models.

Table 4.3 and Figure 4.3 show the results of the different DL models for the classification of crop and weed. CNN model showed the best performance with 98 and 96 per cent yield for weed and crop classification respectively. Recall is one of the important evaluation parameters for agricultural image analysis, which is the ratio of number of TP samples identified to the number of all TP samples. Recall is better the more of the actual crop or weed samples the model is able to identify and the fewer times it fails to identify a sample that is actually a crop or weed. Although lower FP rates are not as vital in precision agriculture, high precision is vital due to the fact that weeds that are not detected can go on growing and competing with the crop for nutrients, water and light, which can reduce the productivity of the crop.

The overall performance of models in terms of recall showed that the most successful one was the Xception architecture. When the two highest recall values (crop recall value 0.93 and weed recall value 0.90) as shown in Table 4.3 are added together, Xception resulted in the highest combined recall value among all the models considered. This is because the Xception employs depthwise separable convolution, a more efficient and less complex way of extracting very discriminative image features. The design can consistently acquire fine scale texture, colour and structural data between crops and

weeds in various environments. The high recall values indicate the high capability of Xception to limit FN, making it very well suited for use in weed detection and precision farming with automation.

VGG19 also showed good recall rates for crops with a crop recall of 0.88 and a weed recall of 0.81. The VGG19 has a deep layered structure, able to capture hierarchical image features, better for recognizing complex patterns of crops. The model proved its usefulness in the field of crop detection and was found to be able to learn the detailed feature representations from data from agricultural fields. However, the relatively low weed recall suggests that the model may sometimes confuse some instances of weeds in a field with something else. In addition, VGG19 has a vast number of trainable parameters, therefore it consumes a lot of memory and is costly for computation time, limiting its application in lightweight and real time agricultural systems.

GoogleNet and DenseNet121 showed a very good and stable recall performance. GoogleNet's crop recall was 0.84 and weed recall was 0.85 while DenseNet121's crop recall was 0.81 and weed recall was 0.83. These models are of good balance in terms of prediction of classification and computation. DenseNet121 has dense feature connectivity for better feature propagation and reuse within the network. GoogleNet also employs inception modules which enable multi-scale feature extraction, for better recognition of various crop and weed patterns. Such architectures can be employed in actual applications in agriculture that have medium computational requirements.

MobileNetV2, U-Net and also EfficientNetB0 had good Recall scores. The recall value for MobileNetV2 was 0.79 and 0.81 for crop and weed, respectively, while U-Net had the values of 0.79 and 0.83 for crop and weed, respectively. These lightweight architectures not only require less computation but are also ideal for embedded systems and real-time weed detection. They do not, however, have the same level of recall as Xception, indicating that they are not as good as Xception at capturing higher level variations in fields and small differences in the appearance of crops and weeds.

ResNet50V2 had the lowest average recall score of 0.74 and 0.76 for crop and weed respectively among all tested models. Similarly, the recall value of the VGG16 model was also comparatively low (0.75 for crops and 0.77 for weed). Low performance of these models might be attributed to the lack of adaptability in complex agricultural scenes, background noise, variations in illumination, and superposition of plants. Lower recall can be indicative of the fact that these models are not capturing a larger percentage of the actual crop and weed scenarios and as such are more likely to be false-negatives. In an actual agricultural condition, this reduction of detection will have a significant impact on the ability of these automated weed management systems to control weeds.

The results given in Table 4.3 and Figure 4.3 are clear that the advanced DL models

which can extract efficient features like Xception are able to outperform the traditional CNN models in the crop and weed classification task based on recall. They can help minimize false detections and enhance feature representation, resulting in more accurate models for use in real-world precision agriculture and intelligent weed management systems.

4.1.4 Comparative Performance Analysis of Deep Learning Models for Crop and Weed Classification

Table 4.4: Comparative Analysis of Deep Learning Models Using Precision, Accuracy, Recall, and F1-score Metrics

S.No	Model	Recall	Precision	Accuracy	F1-score
1	InceptionV3	0.80	0.72	0.78	0.74
2	U-Net	0.75	0.70	0.80	0.72
3	GoogleNet	0.79	0.81	0.76	0.80
4	VGG19	0.70	0.78	0.83	0.77
5	Xception	0.83	0.86	0.85	0.84
6	ResNet50V2	0.78	0.76	0.75	0.78
7	EfficientNetB0	0.83	0.81	0.82	0.80
8	MobileNetV2	0.84	0.82	0.83	0.81
9	VGG16	0.80	0.78	0.79	0.77
10	DenseNet121	0.85	0.84	0.83	0.85

Table 4.4 shows a comparative analysis of the performance of various DL architectures based on four important classification criteria such as recall, precision, accuracy, and F1-score. All these measures provide a general idea of the models' accuracy in crop and weed classification. Recall: model's ability to correctly predict relevant instances for the task; Precision: correctness of predicted classification; Accuracy: overall correctness of the predictions; F1-Score: a balance between Recall and Precision. These metrics can be used together to evaluate the accuracy and reliability of the DL models used in precision agriculture systems.

Out of all the models evaluated, Xception proved to be the best overall. From the results presented in table 4.4, it is seen that Xception has a good recall, precision,

accuracy and F1-score of 0.83, 0.86, 0.85 and 0.84 respectively on all the evaluation parameters. Overall, it is claimed that the depthwise separable convolutions used in Xception enable the extraction of complex features based on spatial and texture, with an efficient reduction of computational redundancy. Under different environmental conditions, there may be very subtle visual differences between crops and weeds in agricultural datasets, and Xception is able to detect these differences well. The remarkable high values of the metrics point toward a successful performance of the model, both in minimizing FP and FN, which makes it a potentially useful system for automated weed detection and intelligent farming systems.

The other two networks DenseNet121 and MobileNetV2 also showed good performance. DenseNet121 had the highest values in terms of Recall and F1 score of 0.85 with high values of Precision and Accuracy. The structure of DenseNet121 is densely connected, which improves the feature propagation and reusability, and makes the model effective to acquire rich feature representations from the agricultural images. Similarly, MobileNetV2 was found to achieve a balanced performance that offer relatively low computation complexity, suitable for real-time and embedded agricultural applications. Also, the efficientNetB0 and GoogleNet showed good efficiency and accuracy of classification.

The accuracy was relatively high (0.83) and the recall was lower than the other high performing models for VGG19. This indicates that for most samples the model can correctly classify the sample type but under more complex field scenarios some crop and/or weed types may not be classified correctly. Also, VGG19 has a huge number of trainable parameters which leads to high computational complexity and high memory consumption. These limitations affect its generality in light agriculture and (near) real time use in the field.

Moderate performance was seen for the evaluation metrics in InceptionV3 and VGG16 models. The comparatively low precision values and F1 scores of these models resulted in meaningful image features, but the models are not particularly good at discriminating between visually similar crops and weeds. But in real agricultural environments they may not be reliable to classify, because of the noise, the different light environments, and overlapping plant areas.

U-Net and ResNet50V2 had the worst overall performance of all the models that have been tested. U-Net performed the worst in terms of precision value (0.70), and also exhibited a lower but decent value for F1 score (0.72), ResNet50V2 had lower values of accuracy but the other metrics values were relatively low. They are not as successful as might be expected due to the difficulty in adapting to very complex agricultural images, and poor discriminative ability of small texture difference between crop and weed. The

lower the metric, the worse the rate of false classifications and how well an automated weed management system is effective.

As a whole, the findings presented in the Table 4.4 clearly show that the advanced DL architectures like Xception and DenseNet121 come with better classification performance because of their efficient feature extraction mechanisms, and their strong generalization ability and robustness in the context of precision agriculture applications.

Chapter 5

CONCLUSION, LIMITATIONS AND FUTURE SCOPE

5.1 Conclusion

Various significant metrics such as precision, recall, accuracy and F1 score were employed to carry out a detailed comparative analysis of various DL architectures for the classification of crop and weed. The experimental results were reached to effective and suitable for crop and weed identification and classification from agricultural field images, which enables the intelligent weed management system to be used in precision agriculture field. The CNN architectures were found to have more reliable performance in terms of reliability in classification, less manual work and sustainable farming practices.

Xception was the best-performing model in all the models evaluated with the maximum overall performance among the different evaluation metrics. The depthwise separable convolution structure of the model has led to better fine-grained spatial and texture feature extraction, which has enhanced the values of precision, recall, accuracy and F1-scores. Xception's ability to correctly and effectively differentiate between visually similar patterns of crop and weeds makes it suitable for the application in automated agriculture. Moreover, DenseNet121 performed well and reliably, suggesting it has potential for being utilized in real-world precision agriculture applications.

However, ResNet50V2 and U-Net have relatively poor performance on the other evaluation parameters. The accuracy, precision, and recall of these models were found to be low hence, there was an indication of the issues associated with feature detection and adaptability of these models to the challenging environmental situations present in agriculture. It can be said that this could result from issues with lighting, background interference, foliage overlap, and even visual differences between crops and weeds.

In summary, it can be stated that DL-based crop and weed classification systems have great potential in improving agricultural output, cutting costs related to labor, and delivering solutions through precision agriculture.

5.2 Limitations

The proposed research exhibits high accuracy with crop and weed classification with DL architecture, but has some drawbacks.

Dataset Dependency: Performance of DL models is strongly dependent on the data set; it needs to be large, diverse and have good quality. The information on agriculture used in this study does not necessarily reflect the actual agriculture practice, such as various weather, light changes, soil properties, thick weeds and seasonal crop changes. Thus, the model may not be applicable in new farming environments.

Computational Complexity: The more powerful models like Xception, DenseNet121 and VGG19, demand more computational power, memory resources and training time. May be too energy hungry to be viable on lower power equipment such as agriculture, embedded systems and real-time robotic weed managements.

Limited Real-Time Implementation: The study was mainly concentrated on image classification offline and not in the real time. The integration of the three key elements of an autonomous sprayer (weed detection, autonomous navigation, spraying) in real-life farming environments, which is still not fully achieved in this work, must be processed quickly and efficiently in real-time.

Environmental Condition Sensitivities: The accuracy of the classification might be affected by various factors including lighting, shadows, background noises, occlusion, overlapping vegetation and motion blur. In some models, the classifiers' performance was decreased in high complexity in field cases.

Restricted Evaluation Metrics: Precision, recall, accuracy and F1-score are the metrics that were taken into account primarily. Apart from the above, other parameters of assessment such as Intersection over Union (IoU), Confusion Matrix analysis, Inference time and computation efficiency can be used to gain insights into the performance and robustness of the model.

Image-Only Classification Approach: The work proposed is not based on any other data, such as multispectral, hyperspectral, thermal or depth data, but only on an RGB set of images. The effectiveness of weed detection however, may be undermined in very complex farming contexts because of the lack of the multimodal sensor integration.

Limited Model Exploration: This study was conducted with the intent to examine the performance of some CNN architectures, but did not consider others that can further enhance the classification performance such as transformer-based, hybrid and self-supervised architectures.

5.3 Future Scope

The following is a list of some areas that may require additional research to develop intelligent crop/weed classification systems.

- **Advanced Deep Learning Models:** In the area of feature extraction and classifying agricultural crops in complex situations, transformer-based models, attention-based models, and hybrid CNN and Transformer models are suggested for consideration.
- **Development of Real-time Weed Detection Model:** The design of light-weight models that can be used in real time on drones, robot weeders and other embedded applications is an area to explore in the future.
- **Multimodal Sensor Integration:** Incorporation of RGB data with hyperspectral, multispectral data, thermal data, LiDAR and depth sensor data to enhance the robustness of the classification and weed detection in difficult environmental conditions.
- **Larger and Diverse Agricultural Datasets:** To enhance model generalizability, more geographically representative and larger-scale agricultural information and data on multiple crop species, various weed species and environmental conditions (weather) should be collected for future research.
- **Semantic Segmentation and Object Detection:** Future systems will be provided with more advanced weed detection algorithms, as well as semantic segmentation, to precisely detect the weed location and, therefore, only spray herbicide when required.
- **Model Optimization Techniques:** Some techniques that can be used to reduce the computation complexity without compromising the classification accuracy are pruning, quantization, knowledge distillation and neural architecture search.
- **The use of Smart Farming Systems:** The deep learning model used for weed classification can be combined with the Internet of Things, self powered tractors and precision spraying system to realize intelligent farming automation and resource-saving farming.

5.4 Social Impact

This proposed DL-based deep learning crop and weed classification system is very much with social and agricultural values in precision farming. With so many people in the

developing world, agriculture is one of the biggest means to sustain their livelihoods. The weed problem remains a serious problem to crop productivity, food quality and economic viability of the farmers. The use of intelligent weed detection systems powered by AI and DL has the potential to significantly enhance agricultural productivity and sustainability.

This study has social implications and it has reduced the use of unindicated herbicides. The traditional approach to weed management has been to spray a blanket application of chemical herbicides over a large area of crop during the growing season, causing pollution of the environment, degradation of soils, contamination of water, and detrimental impacts on human and animal health. In conclusion, the proposed approach to weed classification automation has the potential to enhance weed management strategies and decrease reliance on unnecessary chemical use, thereby fostering sustainable and eco-friendly agricultural practices.

The developed system can also have the potential to reduce the need for farmers' labour and operating cost. Detection and removal of weeds is a time consuming and expensive process particularly in large agricultural fields, and is man intensive in manual weed detection and removal. The automated weed identification system using deep learning technology can identify weeds with high accuracy, helping farmers to efficiently control weeds in the fields with less manual labor. This makes agriculture more efficient and reduces the total cost of production.

Another social implication of conducting such research can be high agricultural productivity and food security. This is because early detection of the weeds prevents any competition between them and crops, and hence the crops remain healthy and produce increased yield. Higher productivity will increase food security for the rising population of the world and benefit the farmers as well.

The suggested framework also enables the development of technologies of smart agriculture and digital farming. The integration of AI tools to automatically identify weeds with drones, IoT sensors, and agricultural robots with autonomous capabilities, along with real-time monitoring, can accelerate the pace of intelligent farming adoption. There is the potential for these technologies to help modernize the traditional agricultural systems and for sustainable rural development.

Moreover, this research also helps to raise awareness and accepting the applications of AI in the agricultural field among researchers, farmers and agricultural industries. It is beneficial to analyse and compare different CNN architectures in detail for the design of efficient and light weight AI system in agriculture that can be used in practical applications.

Overall, the proposed classification of crops and weeds can positively affect social,

economic, technological and environmental aspects and help make farming more efficient, reduce environmental damage, help achieve sustainable agriculture and help develop intelligent precision farming technologies for food production.

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APPENDIX I

I.1 List of Publications

1. **Jatin and Dr. Sanjay Patidar** (2025). "Wheat Crop and Weed Classification Using Deep Learning in Precision Agriculture." *[Scopus Indexed]* [Accepted - NGNDAI-2025, Springer LNNS Series]

2. **Jatin and Dr. Sanjay Patidar** (2026). "Weed Detection in Wheat Fields: A Comparative Study of InceptionV3, U-Net, GoogleNet, VGG19, and Xception." *[Scopus Indexed]* [Accepted - International Conference on Intelligent Computing and Data Science (ICIDS) 2026]

DECLARATION

I hereby certify that the work which is presented in the M.Tech by Research thesis entitled "Wheat Crop and Weed Classification Using Deep Learning in Precision Agriculture" in fulfillment of the requirement for the award of the Degree of Master of Technology (M.Tech) by Research and submitted to the Department of Software Engineering, Delhi Technological University, Delhi, is an authentic record of my own work, carried out during the period under the supervision of Dr. Sanjay Patidar.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in Scopus indexed conference proceedings with the following details:

Paper 1:

Title of the Paper: Wheat Crop and Weed Classification Using Deep Learning in Precision Agriculture
Author Names (in sequence as per research paper): Jatin, Dr. Sanjay Patidar
Name of Conference/Journal: Proceedings of the International Conference on Next-Generation Networks and Deployable Artificial Intelligence (NGNDAI-2025)
Conference Dates with Venue (if applicable): 18 - 20 September, 2025, Motilal Nehru National Institute of Technology Allahabad, Prayagraj
Have you registered for the conference?: Yes
Status of Paper (Accepted/Published/Communicated): Published (Scopus Indexed)
Date of Communication: 25 May 2025
Date of Acceptance: 18 June 2025
Date of Publication: 10 February 2026

Paper 2:

Title of the Paper: Weed Detection in Wheat Fields: A Comparative Study of InceptionV3, U-Net, GoogleNet, VGG19, and Xception
Author Names (in sequence as per research paper): Jatin, Dr. Sanjay Patidar
Name of Conference/Journal: International Conference on Intelligent Data Science (ICIDS-2026)
Conference Dates with Venue (if applicable): 10 - 11 September 2026 at Danang, Vietnam
Have you registered for the conference?: Yes

Status of Paper (Accepted/Published/Communicated): Accepted (Scopus Indexed)
Date of Communication: 15 April 2026
Date of Acceptance: 20 April 2026
Date of Publication: To be published

Roll No.: 24/RSE/11 **Student Signature**
Name: JATIN

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the student is correct.

Place: Delhi
Date: May 20, 2026

Dr. Sanjay Patidar
Supervisor Name and Signature

NOTE: PLEASE ENCLOSE RESEARCH PAPER ACCEPTANCE/PUBLICATION/-COMMUNICATION PROOF ALONG WITH SCOPUS INDEXING PROOF (conference website or ScienceDirect in case of journal publication).

I.2 Paper Acceptance Proofs

I.2.1 First Conference Acceptance Proof

Gmail

JATIN BHARDWAJ <jatinbhardwaj70112@gmail.com>

Review Notification for your Paper ID: 479 under NGNDAI 2025 at MNNIT Allahabad

1 message

NGNDAI 2025 MNNIT <ngndai@mnnit.ac.in> Wed, Jun 18, 2025 at 12:15 AM
To: sanjaypatidar@dtu.ac.in, jatinbhardwaj70112@gmail.com

Dear Authors,

Greetings of the Day !!!

We have received the reports from our reviewers on your manuscript

Paper ID: **479**

Paper Title: **Wheat Crop and Weed Classification Using Deep Learning in Precision Agriculture**

Paper similarity index: 7**%**

Comments: Attached

We are happy to inform you that, based on the reviewer comments, the Programme Committee of NGNDAI-2025 has decided that your paper has been provisionally **accepted** for **oral presentation**. The Proceedings of NGNDAI-2025 will be published as Springer book series "Lecture Notes in Networks and Systems" (LNNS) [indexed by SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago] subject to fulfilling the following:

1. Address reviewers' comments in the revised paper. Along with revised the camera ready paper, submit a separate response sheet to the reviewer's comments.

2. Camera-ready document should be named as "NGNDAI-2025_Paper_YYY"

3. The Subject Line for all the communication hereafter should have paper ID (NGNDAI-2025_Paper_YYY, where YYY is the paper number).

4. It is recommended that the paper should have a minimum of 10 pages in Single-column format. A sample format can be found in the author's guidelines.

5. Please follow the author guidelines for preparing the final manuscript as listed at https://www.springer.com/gp/authors-editors/conference-proceedings

6. Please provide email IDs and full affiliation of all author(s).

7. No salutation should be there in the author list (Dr., Prof., Mr. ..)

8. Similarity Report from Turnitin or iThenticate software to be submitted - overall similarity of less than 15 % excluding references and less than 3% from a single source will only be accepted.

9. Authors have to submit appropriate permissions from a third-party if they are using any third party material/copyrighted material (Figures, Pictures/Tables/Flowcharts etc.). Try to avoid such kinds of figures for smooth production.

10. Authors have to submit the Camera-Ready Copy (CRC doc) in Word or LaTeX and PDF formats both on or before the **25th June 2025** to this sender email.

11. Signed and scanned copy of the "License to Publish" document of Springer Nature to be submitted. [format will be shared soon]

12. Registration is to be completed on or before the **25th June 2025** by visiting: https://www.ngndai.mnnit.ac.in/registration

I.2.2 Second Conference Acceptance Proof

Gmail

JATIN BHARDWAJ <jatinbhardwaj70112@gmail.com>

Acceptance of Your Paper at ICIDS 2026 – Final Submission & Registration Instructions

1 message

Microsoft CMT <noreply@msr-cmt.org> Mon, Apr 20, 2026 at 11:03 AM
To: Jatin Jatin <jatinbhardwaj70112@gmail.com>

Dear Jatin Jatin,

Greetings from ICIDS 2026!

Congratulations! 🎉
We are pleased to inform you that your paper (ID: 182), titled "Weed Detection in Wheat Fields: A Comparative Study of InceptionV3, U-Net, GoogleNet, VGG19, and Xception," has been accepted for presentation and publication at ICIDS 2026.

All accepted and presented papers will be submitted to Springer for inclusion in the Lecture Notes in Networks and Systems (LNNS) series, subject to meeting Springer's scope and quality standards.
📌 Final Submission & Registration Guidelines

You are requested to complete the following steps within 8 days from the date of receiving this email:
✅ Step 1: Review & Revise Your Paper

Log in to your CMT account to view the reviewer comments.

Incorporate all suggested improvements in the final camera-ready version.

Ensure the paper strictly follows the Springer format, available at:
👉 https://icids.in

✅ Step 2: Make the Registration Payment

Use the following link to pay the registration fee:
👉 Payment Link-
https://formbuilder.ccavenue.com/live/ccavenue/manipal-university-jaipur-2/icids-2026

Save the payment receipt – it is required for the registration form.

⚠️ Note: At least one author must register and present the paper (either online or offline) at the conference. Papers without presentation will not be considered for publication.

✅ Step 3: Fill the Registration Form (Post-Payment Only)

After completing the payment, fill the registration form here:
👉 Registration Form Link- https://forms.gle/2ALM8YECSsSYmcaG9

Upload the following in the form:

Payment receipt

Final camera-ready paper (in Springer format, post-revision)

📌 The registration form must be submitted only after payment is made.

Join the Whatsapp Group for further and quick communication-
https://chat.whatsapp.com/Jt5cazW7B1H5zZIRDr4ErQ

⚠️ Important Policies:

I.3 Indexing of Conference Proof

I.3.1 First Conference

Publication

The International Conference on Next-Generation Networks and Deployable Artificial Intelligence (NGNDAI-2025) proceedings will be published as Springer book series "Lecture Notes in Networks and Systems" (https://www.springer.com/series/15179) (indexed in Web of Science, SCOPUS, etc.). **(Approved)**

Selected and extended versions of research papers will be forwarded for publication as a Special Issue in Scopus and SCI/SCIE-indexed Journals of repute.

Best Paper Awards

The Best Paper Award is presented to the authors who have written the best paper among those who appear in the conference proceedings. Recipients are presented with a souvenir and a certificate that describes the award. The awards are announced and bestowed during the conference valedictory session.

I.3.2 Second Conference

PUBLICATION & INDEXING

PUBLICATION

All ICIDS 2026 presented papers will be published in conference proceedings by Springer LNNS. book series "Lecture Notes in Networks and Systems" (LNNS) series, which is indexed by SCOPUS, EI Compendex, INSPEC, WTI Frankfurt eG, zbMATH, and SCImago. **Link**

PAPER SUBMISSION

Authors are kindly invited to submit their formatted full papers including results, tables, figures and references. All submissions are handled through the CMT : **Link**

I.4 Conference Certificates

I.4.1 First Conference Certificate

Next Generation Networks and Deployable AI INDIA-2025

1st International Conference on Next-Generation Networks and Deployable Artificial Intelligence

Certificate

OF APPRECIATION

Jatin

Department of Software Engineering, Delhi Technological University, Delhi

For Presenting Paper, **Wheat Crop and Weed Classification Using Deep Learning in Precision Agriculture** in the **1st International Conference on Next-Generation Networks and Deployable Artificial Intelligence (NGNDAI-2025)** organized by Department of Computer Science and Engineering, Motilal Nehru National Institute of Technology Allahabad, Prayagraj, India on September 18-20, 2025.

Dr. Deepak Gupta
Organizing Secretary

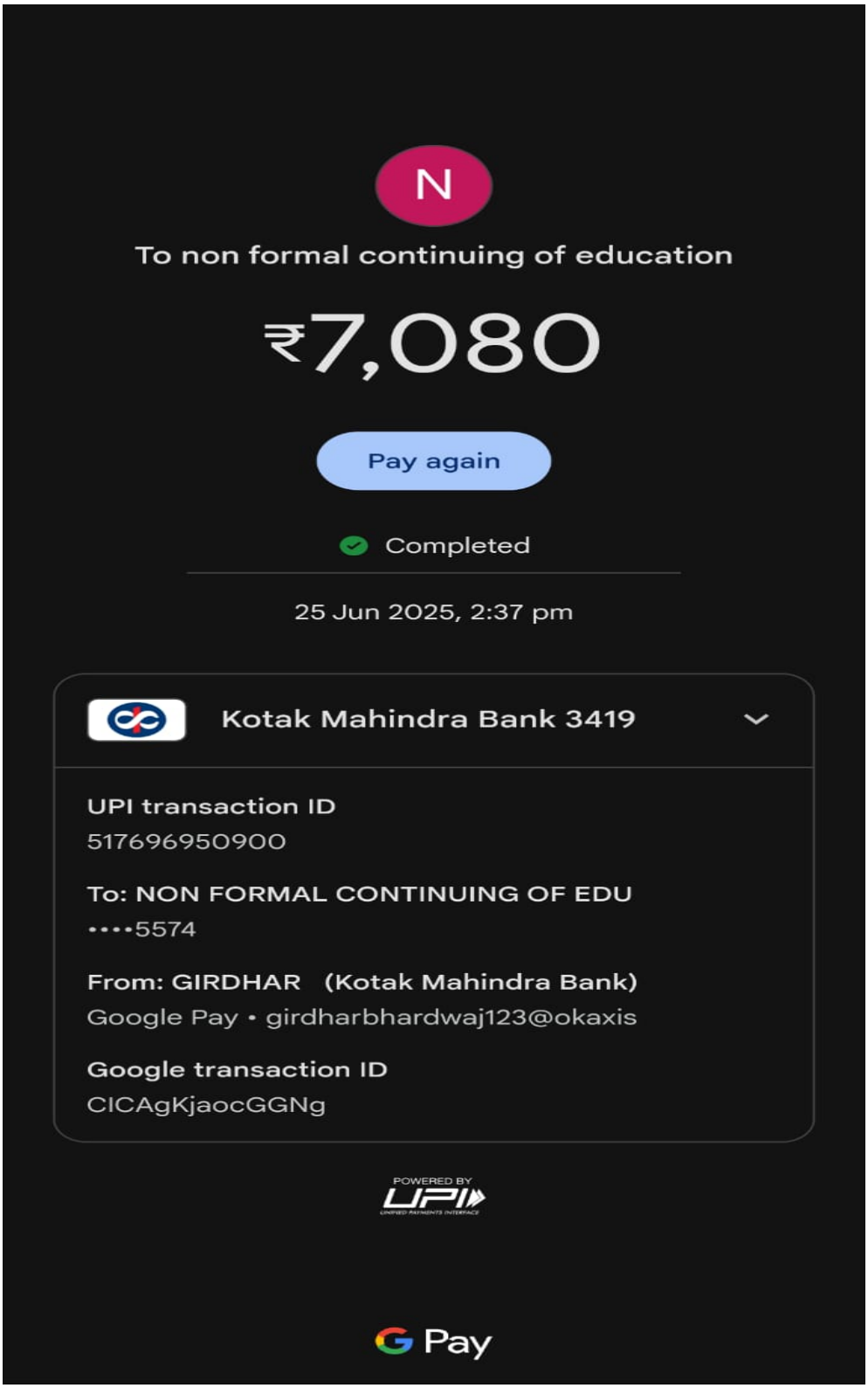
Prof. Mayank Pandey
Organizing Chair and HoD, CSED

I.4.2 Second Conference Certificate

Certificate to be received after the conference (10 - 11 September 2026). Image will be inserted here upon receipt.

I.5 Conference Paper Registration Receipts

I.5.1 First Conference Receipt



I.5.2 Second Conference Receipt

MANIPAL UNIVERSITY JAIPUR

Manipal University Jaipur

Infibeam Avenues

Payment Receipt

Receipt : 114466644900

Date : 2026-04-26 12:11:55

Payer Details

Name	:	Jatin
Email	:	jatinbhardwaj70112@gmail.com
Mobile Number	:	8527996705
University/College	:	Delhi Technological University
Paper Id	:	182
Paper Title	:	Weed Detection in Wheat Fields A Comparative Study of InceptionV3 U Net GoogleNet VGG19 and Xception
Category	:	Research Scholar and Student
Payment	:	Authors from India (in INR)

Fees Details

Amount	:	10011.8

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Order ID	:	7217952
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Currency	:	INR
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AUTHOR'S PROFILE

Jatin is currently pursuing a Master of Technology (M.Tech) by Research from Delhi Technological University (DTU), Delhi, India. His research interests include Artificial Intelligence (AI), Deep Learning, Precision Agriculture, Computer Vision, Weed Detection, Crop Classification, Image Processing, and Intelligent Agricultural Systems.His thesis titled "Wheat Crop and Weed Classification Using Deep Learning in Precision Agriculture" focuses on the development and comparative analysis of advanced Convolutional Neural Network (CNN) architectures for automated crop and weed identification under real agricultural field conditions. The research investigates multiple deep learning models including InceptionV3, U-Net, GoogleNet, VGG19, Xception, ResNet50V2, EfficientNetB0, MobileNetV2, VGG16, and DenseNet121 for accurate classification of wheat crops and weeds using RGB image datasets collected from field environments.

His research primarily focuses on Deep Learning, Computer Vision, Precision Agriculture, Convolutional Neural Networks (CNNs), Image Classification, Weed Detection Systems, Smart Farming Technologies, Agricultural Automation, and Artificial Intelligence-based Decision Support Systems. His post-graduate research work emphasizes the development of intelligent and automated weed detection systems capable of improving agricultural productivity, reducing herbicide usage, and supporting sustainable farming practices through AI-driven image analysis techniques.

He has worked on research papers and conference publications in the fields of artificial intelligence, precision agriculture, crop monitoring, and deep learning-based weed detection systems. His research contributions include comparative analysis of CNN architectures for crop–weed classification, intelligent image-based agricultural monitoring systems, lightweight deep learning frameworks for precision farming applications, and automated classification techniques for real-world agricultural environments.