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Weeds Detection for Agriculture Using Convolutional Neural Network (CNN) Algorithm for Sustainable Productivity

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ABSTRACT

This project aims to develop a weed detection prototype for agricultural settings using the Convolutional Neural Networks (CNN) algorithm. The project thoroughly analyses and optimises CNN hyperparameters to improve accuracy and efficiency, empowering efficient weed control practices. The potential of this algorithm in weed detection is immense, offering a promising future for sustainable productivity in agriculture. Adopting innovative and sustainable agricultural practices is essential for building a robust and productive agriculture sector that can meet future food demands while protecting the environment. The research then assesses how well the CNN model generalises to various agricultural environments that support multiple crop situations. The dataset comprises 360 images of weeds, broadleaf, maise plants, soil and cotton crops. The images underwent four preprocessing phases: image scaling, normalisation, filtering, and segmentation. The proposed model achieved an accuracy of 89.82% utilizing the Convolutional Neural Network (CNN) algorithm, with the dataset partitioned into 80% for training and 20% for testing. Furthermore, the model attained an F1 score of 88.08%, indicating a high degree of alignment between predicted positive instances and actual positive samples. In addition to technological innovations in agriculture, this CNN-based weed detection prototype is a reliable resource for agriculturalists. AI-driven weed detection optimizes resource use, ensuring that pesticides and herbicides are applied only where necessary, reducing chemical overuse. This is in line with the United Nation Sustainable Development Goal (SDG) No. 12.

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INTRODUCTION

Artificial intelligence (AI) and machine learning deal with image recognition, commonly called computer vision (CV) or

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object recognition, which is exciting and is developing quickly (Dosovitskiy et al., 2020). Image recognition is a vital technology with many practical applications since it allows machines to recognise and identify objects, patterns, and features inside digital images (Zoph et al., 2018). It focuses on creating models and algorithms that allow computers to observe, examine, and comprehend visual data from pictures and videos precisely like people do (Hu et al., 2021). Image recognition is essential for improving automation and understanding the world around us in various fields, including autonomous vehicles, healthcare, surveillance systems, and augmented reality (Dosovitskiy et al., 2020).

Various techniques are used in the expanding field of image recognition. Researchers and engineers have created a variety of methods over the years to handle diverse picture recognition problems (Henaff et al., 2020). Firstly, Traditional CV Techniques (Xie et al., 2020). These methods include picture segmentation, feature extraction, and corner and edge detection (Qiao et al., 2018). Next is Convolutional Neural Networks (CNN), a type of deep learning model created expressly for image identification applications (Qiao et al., 2018). They have revolutionised the CV field and are motivated by the structure of the visual cortex in animals (Xie et al., 2020). For image classification, object recognition, and segmentation, CNN automatically learns hierarchical features from raw pixel data (Xie et al., 2020). CNN and deep learning techniques are frequently used for image recognition. These methods have revolutionised the field in recent years because of their capacity to learn intricate patterns and hierarchies from images. CNN is made to automatically and hierarchically learn complex patterns and features from images or other kinds of grid-like input (Sarvini et al., 2019).

Agriculture activities include cultivating crops, raising livestock, and manufacturing food, textiles, and other goods vital for expanding the global population (Ukaegbu et al., 2021). Unwanted weeds have proven to be a detrimental factor in the agricultural industry as they contribute immensely to reducing crop yields, leading to severe economic losses for farmers worldwide (Lottes et al., 2018). These pesky plants can adversely affect crops, depriving them of essential nutrients, water, and sunlight, reducing productivity and quality (Razfar et al., 2022). The agriculture sector faces several significant obstacles that limit its capacity to meet the rising demands and uphold environmental stewardship. The inability to determine the precise location of weeds has led to excessive usage and low utilisation rate of pesticides, causing severe pollution (Xu et al., 2023). Agricultural professionals, including agriculture officers and agronomists, encounter substantial challenges in effectively controlling weeds due to the inherent difficulty in accurately identifying and distinguishing between weeds and crop plants (Wu et al., 2019; Razfar et al., 2022). Traditional agricultural methods often involve manual weed extraction, where farmers use handheld tools such as machetes and hoes to meticulously remove undesired plants from the soil (Asad & Bais, 2020). The motivation for this project stems from the recent use of CNNs in agricultural research, particularly for the early detection of weeds, which can help increase production and reduce costs for farmers.

LITERATURE REVIEW

In the following literature review, this study explores the landscape of the agricultural industry and weeds, focusing on how weed detection can be implemented by utilising computer science advancements.

Agricultural Industry

The agricultural sector is essential in many nations, contributing significantly to their economies' growth and creating many employment possibilities (Wu et al., 2019). Food production, economic growth, and environmental sustainability are all significantly impacted by agriculture, a crucial industry that directly impacts people's lives (Komarek et al., 2020). Several research projects have used machine learning to identify and eradicate weeds. Machine learning algorithms techniques have been used to analyse photos taken in agricultural areas to discriminate between crops and weeds (Xiao et al., 2020). These algorithms develop the ability to identify and correctly classify the visual characteristics of various weed species, but the research's accuracy is still poor (Li et al., 2020). Farming fields are intricate, dynamic settings with various distractions like crop canopy, soil, shadows, and occlusions (Hamuda, 2019). Weed recognition algorithms must consider these elements and differences in lighting, weather, and plant growth stages (Darwin et al., 2021). The difficulty of managing such complexity can affect the detection algorithms' accuracy, and the need for further research in weed detection is urgent and crucial (Ramli et al., 2024).

The need for further research in weed detection is urgent and crucial. The researchers can still learn a lot from these unsuccessful trials and pinpoint areas that need improvement and more research. The improved weed detection research spurs new developments and increases the overall accuracy of weed detection systems. Agriculture has changed dramatically throughout time, utilising technological developments to boost productivity, sustainability, and efficiency (Komarek et al., 2020). According to a United Nations Food and Agriculture Organization (FAO) study, global food production has been rising over time (Boliko, 2019). Approximately 2.76 billion metric tons of cereals were produced worldwide in 2020, with corn, rice, and wheat being the most widely grown crops (Katel et al., 2023). Other than that, it is believed that there are roughly 4.9 billion hectares of agricultural land in the world (Otsuka & Fan, 2021). This land is utilised for farming, including the breeding of cattle and the cultivation of crops (Komarek et al., 2020).

Weeds

Any plant growing where it is not wanted is called a "weed", and the definition of a "weed" is an undesirable plant, out of place, or a problem because it hinders the growth of crops or cattle (De Clercq et al., 2018). Weeds invaded crop-designated regions and were later discovered to possess qualities that were not initially suspected. As a result, they were taken under cultivation and removed from the category of weeds (De Clercq et al., 2018). Weeds frequently display quick growth, a high capacity for reproduction, and the ability to adapt to diverse environmental conditions (Cox et al., 2019). They propagate through seeds, rhizomes, stolons, or other vegetative structures, and they can be annuals, biennials, or perennials (Cox et al., 2019). Three major categories of weeds, in general, are plants with broad leaves and frequently distinguishable flower structures known as broadleaf weeds, and some examples are dandelions, thistles, and plantains (Klerkx et al., 2019). Grass weeds are next and these are weeds that are related to grass and look like them and some examples are crabgrass, foxtail, and barnyard grass (Klerkx et al., 2019). The third categories are Sedges, grass-like weeds, but they may be identified by their solid, three-sided leaves and triangular stems (Klerkx et al., 2019). Nutsedge and yellow nutsedge are two examples (Klerkx et al., 2019). . Weeds are close competitors of crops as they constantly devour water, air, nutrients, and sunlight, which helps the maturation of crops. For better cultivation and good quality production of crops, weed detection at the appropriate time is an essential stride (Singh et al., 2023). Next is grass weeds. These weeds are related to grasses and look like them, and some examples of grass weeds include crabgrass, foxtail, and barnyard grass (Patton, 2023). Lastly, sedges resemble grass but are not the same as grasses because they grow in damp or moist environments and have triangle stems. Nutsedge, yellow nutsedge and kyllinga are typical sedge weeds (Patton, 2023).

Weeds frequently cause farmers to worry that agricultural production may suffer, and, in many cases, weeds consume crop plants' equivalent amounts of nutrients (De Clercq et al., 2018). Additionally, they consume resources like water, sunlight, and space that could have been used for agriculture (Cox et al., 2019). The more similar a crop's needs are to those of weeds, the more they will fight for the same resources, and crop yields will decrease because weeds aggressively compete with them (Anwar et al., 2021). If weeds gain an advantage over the crop, crop yields will be most negatively impacted. Four significant factors are density, timing, size, and chemistry (Lowry & Smith, 2018).

In addition, misusing herbicides or relying too heavily on chemical weed management techniques might harm the environment (Harwood, 2020). Herbicides can affect non-target organisms, such as beneficial insects, wildlife, and aquatic life, contaminate soil and seep into water bodies and herbicide use for weeding management can negatively affect the environment (Ustuner et al., 2020). It can also be expensive and time-consuming for farmers to control weeds (Cox et al., 2019). Herbicide application, manual weed control, and other weed management techniques all demand time, effort, and financial investment (Westwood et al., 2018). For small-scale farmers, weed control can be a significant financial strain, and weeding requires much labour (Woyessa, 2022).

Role of Computer Science in Weed Management

Weed management is a critical aspect of precision agriculture, and computer science plays a vital role in enhancing efficiency, accuracy, and sustainability in this domain. Weed control is vital to modern agriculture to ensure the best crop development and output (Chegini et al., 2023). However, conventional weed control methods can entail lengthy, labour-intensive procedures and excessive pesticide use, which can harm the environment (Pervaiz, 2024). The fusion of computer science and weed management has been a potential area for creating novel and long-lasting solutions in recent years (Prathima & Varshini, 2024). With its wide range of algorithms, machine learning methods, and cutting-edge sensing technologies, computer science has enormous potential to transform weed management practices (Jinglei et al., 2017). Researchers and practitioners can improve weed management practices' effectiveness, accuracy, and sustainability by utilising computational tools, which will increase agricultural productivity and have less negative impact on the environment (Vasileiou et al., 2023).

Innovative weed detection, classification, mapping, and targeted removal methods can be developed using computer scientific methodologies like machine learning, image processing, robotics, and data analytics (Jinglei et al., 2017). Machine learning techniques have much potential for weed detection (Islam et al., 2021). These algorithms may learn to distinguish between crops and weeds by being trained on large datasets of annotated weed photos, accurately recognising and outlining weed-infested areas inside agricultural fields (Shorewala et al., 2021). CV techniques can help with weed detection and create automated robotic systems that selectively recognise and remove weeds (Haichen et al., 2020). These autonomous robots can walk through fields, recognising and mechanically eradicating weeds while sparing important crops since they are outfitted with machine-learning algorithms (Vasileiou et al., 2023).

Computer science approaches can be used to analyse and interpret high-resolution imaging and spectral data, enabling prompt and precise weed species identification, growth stage monitoring, and forecast (Ghazal et al., 2024). Although there is great potential for combining computer science and weed management, several issues must be resolved (Dong et al., 2021). These include the necessity for interdisciplinary partnerships between agronomists, computer scientists, and engineers, algorithm robustness in shifting environmental circumstances, computing constraints for real-time applications, and data collection and annotation (Voutos et al., 2019).

Image Recognition

A CV technique called image recognition, commonly referred to as object detection, is used to find occurrences of objects in pictures or movies (Hall et al., 2020). Image detection algorithms frequently use machine learning or deep learning to generate valuable results. Humans can quickly identify and pinpoint objects of interest when viewing photos or videos (Hall et al., 2020). Image detection aims to automate the replication of this intelligence, and it involves locating and detecting objects or features inside an image or a video (Mohan & Poobal, 2018). It is crucial in numerous applications, such as augmented reality, surveillance systems, driverless vehicles, and facial recognition (Li et al., 2020).

A deep learning-based method, notably those based on CNN, has become extremely popular and has attained outstanding results in recent years. Due to its high computational requirements, implementation in edge devices becomes challenging. Cloud computing serves as an enabler, allowing devices with limited resources to perform deep learning (Tan et al., 2022). Furthermore, developing frameworks like TensorFlow, PyTorch, and OpenCV offers significant tools and resources for creating image detection systems (Hall et al., 2020). These frameworks include pre-trained models for object detection in pictures or videos, which can be adjusted or applied immediately (Murthy et al., 2020). They also offer Application Programming Interfaces (API) and GUI to make it easier to incorporate picture-detecting capabilities into various applications (Li et al., 2020).

Every object class has unique characteristics that aid in identifying the class. For instance, searching for circles is expected to seek items a specific distance from the circle's axis (Traore et al., 2018). Similar to searching for squares, finding items with equal side lengths and perpendicular corners is necessary (Traore et al., 2018). Object detection techniques typically fall into two categories: neural network-based or non-neural methods (Xiao et al., 2020). For non-neural approaches, it is required first to define features using one of the techniques listed below and then perform the classification using a method like Support Vector Machine (SVM) (Li et al., 2020). On the other hand, neural approaches, which are frequently based on CNN, can do end-to-end object detection without directly defining features (Li et al., 2020).

Image Recognition Techniques

In the realm of image recognition, conventional machine learning methods rely on approaches such as Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), and Local Binary Patterns (LBP) to extract pertinent features from images. CNN has revolutionised the field by autonomously learning intricate hierarchical representations directly from pixel data via convolutional, pooling, and fully connected layers. CNN is proof of the evolution of Artificial Neural Networks (ANN), which are mainly used to extract features from datasets with grid-like matrixes (Li et al., 2020). Examples of visual datasets where data patterns play a significant role are images and videos (Gu et al., 2018). Artificial neurons, also known as units, are found in artificial neural networks, and units are connected from one layer to another (Yamashita et al., 2018). Each linkage has weights that control how much one unit influences another, and the neural network learns more and more about the data as it moves from one unit to another, eventually producing an output from the output layer (Tan & Le, 2019).

Although there are different kinds of neural networks in deep learning, CNN is the preferred network architecture for identifying and recognising objects (Tan & Le, 2019). Therefore, they are ideally suited for CV activities and applications where accurate object recognition is crucial, such as facial and self-driving automobile systems (Tan & Le, 2019). CV, which uses one or more video cameras, analogue-to-digital conversion (ADC), and digital signal processing (DSP), is the ability of a computer to see (Li et al., 2020). Machine vision's complexity is comparable to speech recognition (Zhou, 2020). Cameras are used by machine vision to collect visual data from the environment and then prepare the data for usage in various applications by processing the photos using a combination of hardware and software (Gu et al., 2018). Specialised optics are frequently used in machine vision technology to capture images; with these methods, specific aspects of the image can be processed, examined, and assessed (Zhou, 2020). The implication of the convergence of weed control and computer science is the intriguing potential to revolutionise agricultural practices. We can develop more precise, effective, and sustainable weed management strategies by embracing cutting-edge technologies and computational tools.

MATERIALS AND METHODS

This study divided the methodology into three phases: data preparation, algorithm implementation, and performance evaluation. Figure 1 visually represents the three phases: Phase 1: Dataset preparation, Phase 2: Algorithm Implementation, and Phase 3: Performance Evaluation.

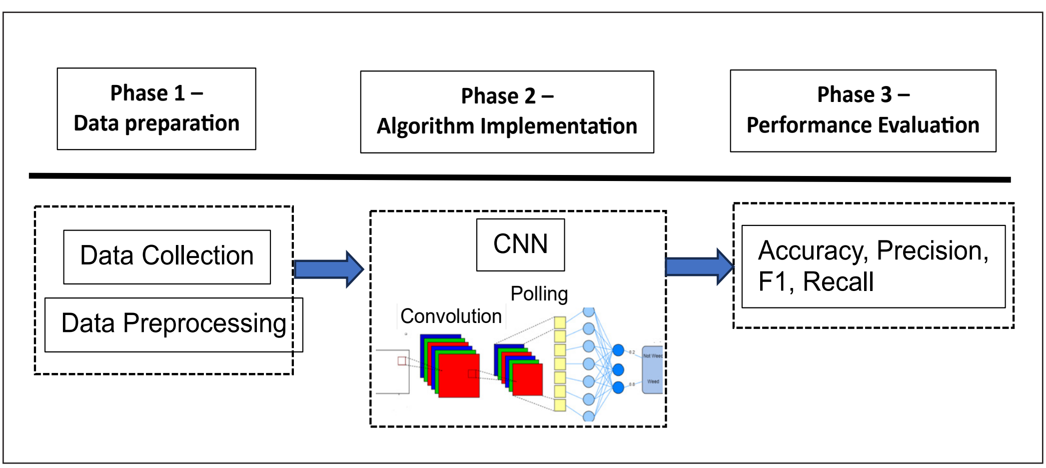

Figure 1. Research methodology

Phase 1: Data Preparation

Data Collection

It is crucial to ensure that the dataset accurately depicts real-life situations that can be anticipated when running into them during inference. It should include a variety of weed species, stages of growth, lighting, backgrounds, and viewpoints. A dataset was chosen based on research conducted by Uchechi F. Ukaegbu at the University of Johannesburg in South Africa. The dataset collection for automatic weed detection and identification came from Yuzhen Lu of the Department of Agricultural and Biological Engineering. The annotated visual dataset for this dataset is now accessible via Kaggle and the repository. The dataset of images of cotton crops, weeds, maise and wheat crops, chilli and jute crops was collected using unmanned aerial vehicles (UAVs) with an input shape of 224×224×3 and a batch size of 20. This data collection has 360 images and a total size of 83 MB. There are 360 total images in the dataset. 80% of the dataset are images used for training, while the remaining 20% are used for testing and evaluation. Based on research by Hosein Chegini from the University of Auckland, who used a training dataset of 77% and a testing dataset of 23% from 500 photos and achieved an accuracy of 95%, this division was created.

Data Preprocessing

Raw data is subjected to several techniques and activities known as dataset preprocessing before being utilised to train a machine-learning model. It requires transforming and altering the data to guarantee that it is in an appropriate format for analysis and modelling. Enhancing the data's quality, consistency, and usefulness for training a CNN model requires dataset preparation. This enhances the model's capacity to discover significant patterns, generalise fresh data well, and produce reliable forecasts in practical situations. The goal of dataset preparation is to format the data for training a machine learning model. It helps improve model evaluation, enhances feature representation, reduces noise or inconsistencies, and ensures data quality.

Image resizing is a common preprocessing step in machine learning projects. It involves changing the image's dimensions while keeping its aspect ratio to avoid distortion. A typical method for resizing is scaling, which adjusts the width and height, using interpolation techniques like bilinear or bicubic to maintain quality. Another method is cropping, where a region of interest (ROI) is selected and resized. Image normalisation helps standardise pixel values, making the model more resilient to lighting or colour changes and aiding training. One type of normalisation is min-max normalisation, which scales pixel values to a specific range, usually between 0 and 1. Histogram equalisation improves image contrast by redistributing pixel values to a new range. This technique is useful for images with low contrast or uneven lighting.

Image filtering is a common technique in image processing used to enhance or modify an image's visual qualities. It involves applying a filter or kernel to each pixel using methods like convolution or correlation. Image filtering is used for noise reduction, edge detection, smoothing, sharpening, and feature extraction. A Gaussian filter smooths the image by reducing high-frequency noise while preserving its structure. It gives higher weight to pixels near the centre, creating a blurring effect. Sobel and Prewitt filters are often used for edge detection by calculating the gradient's size and direction at each pixel, highlighting areas with rapid intensity changes. Image segmentation divides an image into meaningful sections. Thresholding is a basic segmentation method that assigns pixels to different segments based on intensity values, best used when objects stand out from the background. Edge-based segmentation finds the borders between different regions by detecting sudden changes in pixel intensity. Popular edge detection techniques include the Laplacian of Gaussian (LoG) and the Sobel operator.

Phase 2: Algorithm Implementation

The dataset consists of images of weeds, broadleaf, maise plants, soil, and cotton crops that go through a few processes, based on Figure 2. The 360-image dataset was split into two categories: 80% dataset for training and 20% dataset for testing. This partition was based on research by Dong Hu using data from 22177 images of 12 rice weeds. Dong Hu from Shanghai Ocean University in China selected to use a 74% training and 26% testing dataset for his study (Dong et al., 2021). The result showed that the accuracy was 81% (Dong et al., 2021).

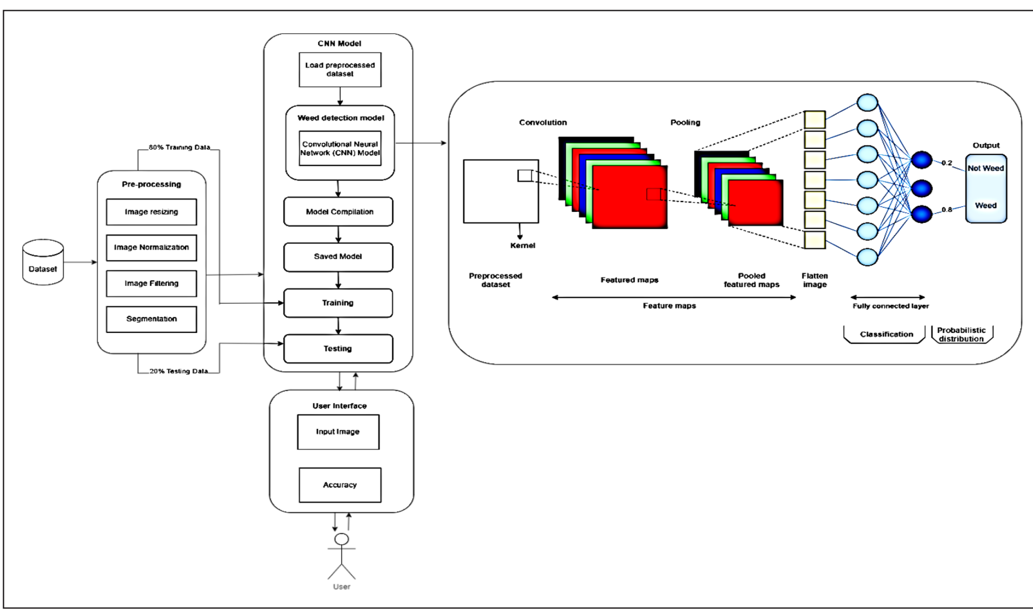

Figure 2. Prototype architecture of weed detection for agriculture using CNN algorithm

After preprocessing the weed image successfully, it will move on to the CNN model training. Using the preprocessed dataset to train a machine-learning model is a practice known as "Dataset training." The major source of information for the model is that it discovers patterns and relationships in the input data and their associated labels. The goal is to enable the model to accurately predict or categorise novel, unanticipated inputs. The model can generalise and predict cases it has not encountered before due to the training process, which teaches it the data's underlying patterns, relationships, and representations. The CNN model includes taking the dataset photos. It applies a filter or kernel to the input image during the convolution process to identify and extract specific characteristics. The pooling layer then reduces the spatial dimensions of the feature maps produced by the convolutional layer. It down-sampled the data to reduce the size of the feature maps and the computational difficulty.

The activation layer then applies a non-linear activation function, such as the ReLU function, to the output of the pooling layer. The nonlinearity generated by this function allows the model to learn increasingly complex representations of the input data. Next is the layer that is entirely interconnected. In a typical neural network layer, every neuron in the layer before is connected to every neuron in the layer after. This layer combines the learned information from the convolutional and pooling layers to provide a prediction (Goodfellow, 2016). The dense layer can then merge the features that the convolutional and pooling layers combined to extract from the input image, producing the final prediction. The dense layer in a CNN is often the last used to generate the output predictions. The dense layer conducts a weighted sum of the inputs. It employs an activation function to generate the final output after flattening and passing the activations from the layers before it as inputs. The dataset will be tested when the CNN model has been built. The goal of dataset testing is to gauge how effectively the model works with unknown data and predict how effective it will be in practical situations. During this phase, the accuracy of the CNN model will be calculated and analysed using the confusion matrix.

Finally, the user interface will display the accuracy to be analysed, whether there is an image of a weed. Typically, accuracy is given as a percentage. A model score is a number or statistic used to determine the degree to which a prediction model works. These results show how effectively the model can predict outcomes based on brand-new, unforeseen data. For instance, an accuracy of below 50% denotes that the system cannot detect any weed's presence in the input data. However, the weeds are detected if the accuracy is above 50%.

Pseudocode

Before the CNN algorithms are implemented in a programming language, the weed detection prototype pseudocode is primarily intended to simplify the design, planning, and communication of the CNN algorithms inside the prototype. By offering a more accessible and intelligible representation of an algorithm than formal programming language syntax, pseudocode plays a crucial role in software development. It enables programmers to pay attention to the logic and flow of the algorithm rather than becoming sidetracked by language-specific features. The pseudocode is shown in Figure 3.

```
Input:
  Crop field images
Output:
  Weed Detection
Start
  1. Input Weeds Dataset
  2. Data preprocessing
     - Image resizing
     - Image normalization
     - Image filtering
     - Image segmentation
  3. Dataset splitting
     - 80% training set
     - 20% testing set
  4. Training the CNN model
  5. Testing CNN model
  6. Detecting weed from the user input
        if accuracy >=50%
          print("Weeds detected in the image.")
          print (accuracy)
        else
          print("No weeds detected in the image.")
          print (accuracy)
End
```

Figure 3. Pseudocode

This pseudocode describes how to train a CNN model to recognise weeds in photographs of crop fields and how to use the model to forecast the presence of weeds in fresh images supplied by the user. The accuracy score determines weed detection, and the results are printed accordingly. Weeds datasets are the prototype's inputs (images). The weed detection algorithm will be trained and tested using these images. Weed detection is the prototype's output. The main objective of the pseudocode is to detect weeds in the input crop field images. The system will determine whether weeds are present in the input images. The pseudocode's primary goal for the input images is to detect weeds. The prototype will determine whether weeds are visible in the supplied dataset.

The dataset is divided into two parts: 20% is used to test the model's performance, and 80% is used to train the model. With this split, the model is trained on a sizable dataset and given access to unused data for evaluation. The CNN training model then starts. CNNs are particularly well-suited for image-related tasks due to their ability to learn and recognize spatial feature hierarchies. The CNN model will be trained using the provided dataset, where the training data is fed into the model during the training phase. The model discovers weed-related patterns and traits through an iterative optimisation procedure. The model's performance is assessed following training using the testing dataset. This process enables evaluation of the model's ability to generalise to unseen data.The model is prepared to be utilised for weed detection on user-provided input photos after it has been trained and tested.

The model gives accuracy by reflecting its confidence level in a prediction when it produces one based on an image the user has provided. The pseudocode interprets a positive detection of weeds as one for which the accuracy is greater than or equal to 50%. This message ("Weeds detected in the image.") will be printed if the model finds weeds in the input image. The accuracy score, which expresses how confident it is in detecting weeds, is printed to provide further details. The pseudocode classifies weed detection as negative if the accuracy of finding it is lower than 50%. This message ("No weeds detected in the image.") will be printed if the model determines that there are no weeds in the input image in this circumstance. Additionally, the model's rating for the negative detection is printed.

Evaluation Phase

The performance of the model was tested throughout the evaluation phase. The evaluation phase is a step in the machine learning process when evaluation metrics and methodologies are used to gauge the performance of a trained model. The objectives of the evaluation phase are to gain knowledge of the model's performance, comprehending its advantages and disadvantages, and assessing its suitability for the intended job or application. The evaluation of a CNN model's performance on a test dataset is called a CNN accuracy test. The accuracy with which the CNN model predicts the classes for the test samples is what is measured. Since accuracy clearly indicates the model's general correctness, it is a crucial evaluation statistic. The number of accurate forecasts divided by the total number of predictions is used to compute it. High accuracy means the model correctly predicts values from the testing dataset. As a result, the confusion matrix might offer more profound perceptions about the model's effectiveness. The confusion matrix is illustrated in Figure 4.

A confusion matrix evaluates the performance of a classification model by presenting its predictions, including true positives, true negatives, false positives, and false negatives

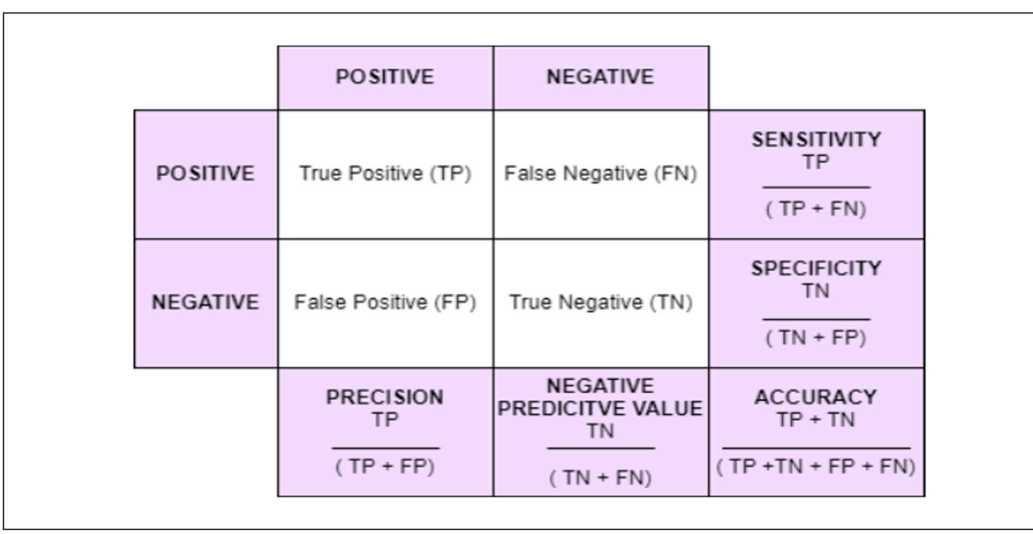

Figure 4. Confusion matrix

(Powers, 2011). It includes details on both actual and anticipated classifications. The number of accurately anticipated positive instances or observations is measured by the term "True Positive" (TP). The number of accurately anticipated negative occurrences or observations is True Negative (TN). False Positive (FP) counts the number of instances or observations wrongly projected to be positive. These are situations that the model mistook for positive ones, even if they are genuinely harmful. Finally, False Negative (FN) displays how many negative data instances or observations were mispredicted. This refers to instances where the model incorrectly classified positive cases as negative.

It indicates how many instances of positivity the classifier has classified as such. The outcome ought to be better. The following term for specificity is the True Negative Rate. It measures how many negative examples the classifier is classified as such. There needs to be much specificity. The ratio of the total number of positively classified positive examples to the total number of positively forecasted positive examples is known as precision. It demonstrates that a favourable prediction was accurate. The accuracy formula then multiplies the total number of instances, equal to the sum of the true positives, false positives, true negatives, and false negatives, by the number of true positives and true negatives. Concerning the overall number of cases, it measures how effectively the model predicts positive and negative examples.

RESULTS AND DISCUSSIONS

The first step is evaluating the accuracy of the CNN algorithm that has been put into practice and analysing how well it performs in weed detection. The second part thoroughly examines the CNN model to determine its general effectiveness and accuracy in weed identification. The third and final section tests the weed detection prototype interface, examining its workings and ensuring everything works.

Evaluation of the CNN Model

A crucial aspect of evaluating the CNN model for weed detection is evaluating the model through dataset splitting. A split of 70–30 is commonly employed, where 70% of the data is designated for training, and the remaining 30% is reserved for testing. This approach ensures that the model's performance generalises effectively to new, unseen data. Table 1 provides a comprehensive overview of accuracy results obtained from different splitting configurations, including 70–30, 80–20, and 90–10, executed over 15 epochs. Upon analysis of the table, it becomes evident that the optimal dataset splitting for the best accuracy is achieved when 80% of the data is allocated for training and 20% is set aside for testing. This configuration produces an accuracy of 89.82% for training and 94.37% for testing after 15 epochs. The findings suggest that the 80–20 split strikes the right balance, facilitating good model performance in weed detection.

Table 1
Evaluate the CNN model with different splits

Total dataset	Data splitting				Epochs	Training accuracy	Testing accuracy
	Training		Testing				
	Percentage	Number of datasets	Percentage	Number of datasets			
360 images	70%	252	30%	108	15	88.37%	97.2%
	80%	288	20%	72		89.82%	94.37%
	90%	324	10%	36		89.16%	97.14%

As Figure 5 demonstrates, the model outperformed the results obtained with the 70–30 and 80–20 splits, achieving an accuracy of 89.82% with 15 epochs. Considering that this specific model's training process took several hours is relevant. Because of the significant size of the datasets and technological limitations, the maximum number of epochs tested was limited to 15. Despite these limitations, the accuracy of 89.82% attained with the 15-epoch configuration demonstrates the model's performance under the specified circumstances.

Figure 6 presents a graphical representation of the accuracy achieved with an 80% training dataset, utilising 15 epochs for 360 image datasets. The graph portrays an upward trend, indicating a consistent increase in accuracy over the training period. This visual representation is a valuable tool for assessing the model's performance, demonstrating its ability to learn and improve accuracy as the training epochs progress. The graph's ascending

```
Epoch 1/15
8/8 [==============================] - 3s 75ms/step - loss: 0.6735 - accuracy: 0.6195 - val_loss: 0.6476 - val_accuracy: 0.8070
Epoch 2/15
8/8 [==============================] - 0s 20ms/step - loss: 0.6220 - accuracy: 0.7920 - val_loss: 0.6017 - val_accuracy: 0.8070
Epoch 3/15
8/8 [==============================] - 0s 19ms/step - loss: 0.5816 - accuracy: 0.8319 - val_loss: 0.5670 - val_accuracy: 0.8246
Epoch 4/15
8/8 [==============================] - 0s 18ms/step - loss: 0.5497 - accuracy: 0.8186 - val_loss: 0.5434 - val_accuracy: 0.8070
Epoch 5/15
8/8 [==============================] - 0s 18ms/step - loss: 0.5143 - accuracy: 0.8186 - val_loss: 0.5131 - val_accuracy: 0.8596
Epoch 6/15
8/8 [==============================] - 0s 19ms/step - loss: 0.4798 - accuracy: 0.8451 - val_loss: 0.4797 - val_accuracy: 0.8421
Epoch 7/15
8/8 [==============================] - 0s 18ms/step - loss: 0.4489 - accuracy: 0.8451 - val_loss: 0.4538 - val_accuracy: 0.8421
Epoch 8/15
8/8 [==============================] - 0s 19ms/step - loss: 0.4191 - accuracy: 0.8540 - val_loss: 0.4275 - val_accuracy: 0.8246
Epoch 9/15
8/8 [==============================] - 0s 20ms/step - loss: 0.3965 - accuracy: 0.8717 - val_loss: 0.4106 - val_accuracy: 0.8246
Epoch 10/15
8/8 [==============================] - 0s 22ms/step - loss: 0.3795 - accuracy: 0.8761 - val_loss: 0.4001 - val_accuracy: 0.8421
Epoch 11/15
8/8 [==============================] - 0s 17ms/step - loss: 0.3675 - accuracy: 0.8673 - val_loss: 0.3987 - val_accuracy: 0.8421
Epoch 12/15
8/8 [==============================] - 0s 19ms/step - loss: 0.3514 - accuracy: 0.8628 - val_loss: 0.3851 - val_accuracy: 0.8421
Epoch 13/15
8/8 [==============================] - 0s 18ms/step - loss: 0.3404 - accuracy: 0.8761 - val_loss: 0.3746 - val_accuracy: 0.8421
Epoch 14/15
8/8 [==============================] - 0s 18ms/step - loss: 0.3310 - accuracy: 0.8982 - val_loss: 0.3682 - val_accuracy: 0.8421
Epoch 15/15
8/8 [==============================] - 0s 18ms/step - loss: 0.3229 - accuracy: 0.8982 - val_loss: 0.3666 - val_accuracy: 0.8421
INFO:tensorflow:Assets written to: saved_model/my_model\assets
```

Figure 5. Training epoch

trajectory indicates the model's effectiveness in capturing patterns and features within the dataset, ultimately improving accuracy. Furthermore, it is observed that increasing the number of training epochs tends to enhance accuracy. The highest accuracy recorded is 89.82%, achieved with 15 epochs. The model still delivers commendable accuracy at 86.01% for a more time-efficient approach with five epochs. Interestingly, utilising ten epochs does not significantly alter the performance, maintaining accuracy levels akin to those achieved with five epochs.

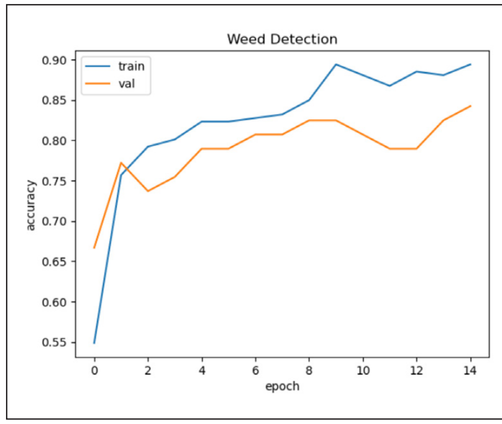

Figure 6. Graph of accuracy for 80% training dataset

Table 2 illustrates this comparison across different epoch configurations. The results indicate that an 80–20 dataset split, coupled with a judicious choice of epochs, significantly contributes to the model's accuracy and efficiency in identifying weeds.

Table 2
Evaluate the CNN model with different epochs

Total dataset	**Data splitting**				**Epochs**	**Testing accuracy**
	Training		**Testing**			
	Percentage	**Number of datasets**	**Percentage**	**Number of datasets**		
360 images	80%	288	20%	72	5	86.01%
					10	86.71%
					15	89.82%

Model Performance

Figure 7 shows that the accuracy of the CNN model is 0.9014, indicating that 90.14% of the model's predictions are correct. Precision, measured at 0.9394, signifies that 93.94% of the samples identified as weeds by the model were indeed weeds. The recall of 0.8611 indicates that the model accurately identifies weeds 86.11% of the time when predicting a sample as a weed. The F1 score, an average of accuracy and

```
3/3 [==============================] - 0s 5ms/step
Confusion Matrix (CNN):
[[31  2]
 [ 5 33]]

Classification Report (CNN):
              precision    recall  f1-score   support

           0       0.86      0.94      0.90        33
           1       0.94      0.87      0.90        38

    accuracy                           0.90        71
   macro avg       0.90      0.90      0.90        71
weighted avg       0.90      0.90      0.90        71
```

Figure 7. Calculation of accuracy by the prototype

recall, is computed at 88.08%, serving as a comprehensive measure of the model's overall performance.

Prototype Interface

The user interface for the weed detection prototype was developed using Tkinter, providing a visually intuitive and user-friendly experience. Figure 8 illustrates the graphical user interface (GUI) that comprises three main buttons. The "Upload Image" button allows users to select and upload an image displayed within a designated box on the interface. The "Start" button initiates the weed detection algorithm, leveraging a pre-trained CNN model (new_model) previously trained on a weed detection dataset. The accuracy of the detection process is showcased, providing valuable insights into the model's performance. As shown in Figure 8, if a user inputs an image containing weeds, the system successfully detects the weeds and displays the accuracy of the CNN model.

Conversely, in Figure 9, if a non-weed image is selected, the system accurately identifies the absence of weeds and presents the corresponding model accuracy.

DISCUSSION

The evaluation of our weed detection system, employing CNN algorithms, reveals an accuracy of 89.51%. To contextualise our findings, we compare notable studies in the field. Table 3 presents a summarised comparison of the findings with previous research. This indicates that the research conducted in this project is in line with previous studies, achieving an accuracy of 89.82%. This highlights the effectiveness of the CNN-based

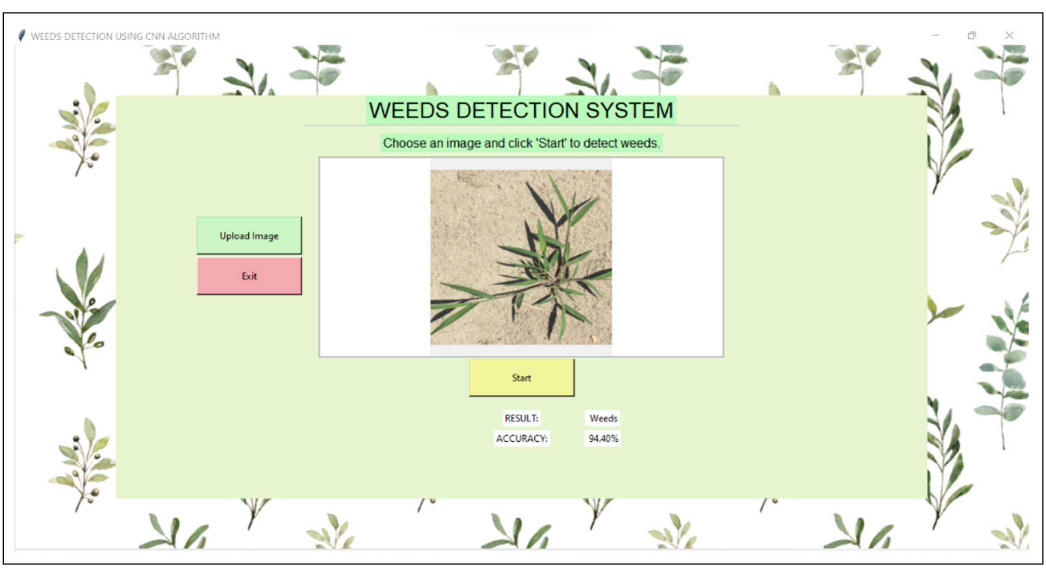

Figure 8. User interface with weeds as input User interface with weeds as input

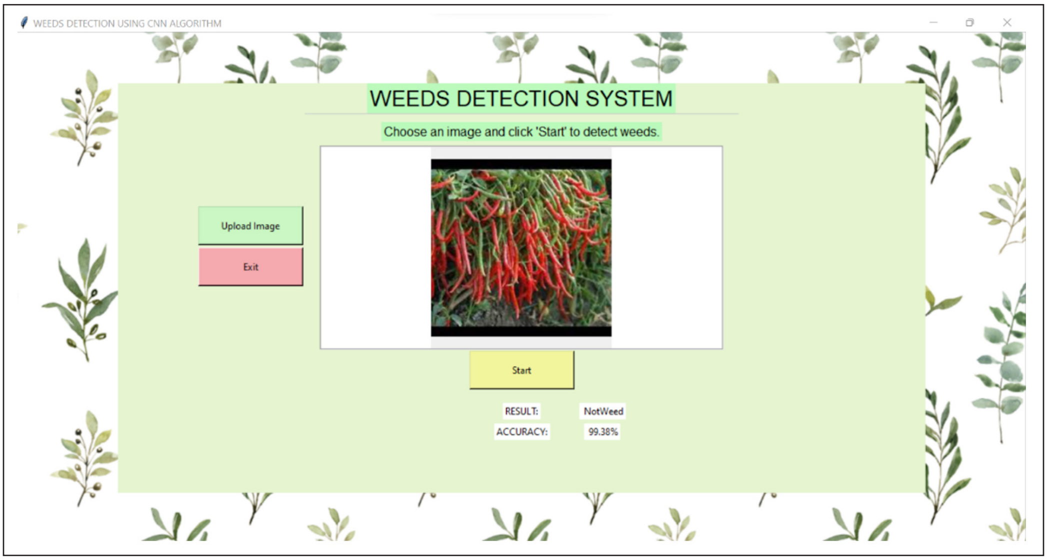

Figure 9. User interface with weeds as input, User interface with no weeds as input

Table 3
Discussion on previous research

No.	Title	Year	Result	Reference
1.	Weed Detection in Farm Crops Using Parallel Image Processing	2018	91.1%	Umamaheswari et al. (2018)
2.	Weed Classification in Hyperspectral Remote Sensing Images Via Deep Convolutional Neural Network	2018	88%	Farooq et al. (2018)
3.	Weed Seedling Detection Using Mask Regional Convolutional Neural Network	2020	98%	Patidar et al. (2020)
4.	Designing and Developing a Weed Detection Model for California Thistle	2023	95%	Chegini et al. (2023)

weed detection system and places it in a favourable position among notable endeavours in the field. As we delve into the details of our methodology, it becomes clear that our approach has yielded promising outcomes, making a valuable contribution to the continuous advancement of weed detection technologies.

CONCLUSION

To summarise, the project highlights the significant potential of Convolutional Neural Networks (CNN) in weed detection for precision agriculture. The successful accomplishment of the project demonstrates the robustness of the implemented CNN algorithms and their application in addressing the intricacies associated with weed identification in agricultural settings. The model architecture, input representation, and user-friendly graphical interface are all seamlessly integrated into the prototype of the CNN model. A user-friendly prototype successfully identified weeds in agricultural images and functioned as a valuable tool for agriculturalists. A thorough evaluation demonstrated how accurate CNN's weed detection algorithms are. Specific testing procedures, such as confusion matrix analysis and dataset splitting, were used. Along with precision, recall, and F1 score metrics, the accuracy of 89.87% indicates the effectiveness of the developed CNN model in accurately identifying weeds in various agricultural contexts.

The effective CNN-based weed detection prototype solved another problem highlighted: the challenges of accurately identifying and managing weeds. The prototype's accuracy of 89.87% for splitting 80–20, proven by thorough evaluation metrics, allows weed control in agriculture to be effectively and practically addressed. CNN's demonstrates potential performance underscores its relevance in precision agricultural research. The outcome of this project fosters agricultural innovation by integrating AI and machine learning into farming practices, encouraging technological advancements in the agricultural sector. Future research can explore the integration of CNN and LSTM algorithms, specifically for weed detection, with the goal of enhancing model performance and accuracy.

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