This is a “preproof” accepted article for Weed Science. This version may be subject to change in the production process, *and does not include access to supplementary material*.
DOI: 10.1017/wet.2024.109

Rapid Detection of Acetolactate Synthetase Inhibitor Resistant Weeds Utilizing Novel Full-Spectrum Imaging and a Hyperparameter-Tuned Convolutional Neural Network (CNN)

Pauline Victoria Estrada[1], John Benedict Estrada[2], Jennifer Valdez-Herrera[3], and Anil Shrestha[4]

[1]Student, Clovis North High School, Fresno, CA, USA, [2]Undergraduate student, University of California - Berkeley, College of Computing, Data Science, and Society, Berkeley, CA, USA, [3]Graduate student, California State University - Fresno, Department of Plant Science, Fresno, CA, USA and [4]Professor (ORCID 0000-0001-7709-6344), California State University - Fresno, Department of Plant Science, Fresno, CA, USA

Author for correspondence:
Anil Shrestha; Email: ashrestha@mail.fresnostate.edu

Short title: AI herbicide-resistant weeds

Abstract

Herbicide-resistant weeds are fast becoming a substantial global problem, causing significant crop losses and food insecurity. Late detection of resistant weeds leads to increasing economic losses. Traditionally, genetic sequencing and herbicide dose-response studies are used to detect herbicide-resistant weeds, but these are expensive and slow processes. To address this problem, an artificial intelligence (AI)-based herbicide-resistant weed identifier program (HRIP) was developed to quickly and accurately distinguish acetolactate synthetase inhibitor (ALS)-resistant from -susceptible common chickweed plants. A regular camera was converted to capture light wavelengths from 300 to 1,100 nm. Full spectrum images from a two-year experiment were used to develop a hyperparameter-tuned convolutional neural network (CNN) model utilizing a “train from scratch” approach. This novel approach exploits the subtle differences in the spectral signature of ALS-resistant and -susceptible common chickweed plants as they react differently to the ALS herbicide treatments. The HRIP was able to identify ALS-resistant common chickweed as early as 72 hours after treatment at an accuracy of 88%. It has broad applicability due to its ability to distinguish ALS-resistant from -susceptible common chickweed plants regardless of the type of ALS herbicide or dose used. Utilizing tools such as the HRIP will allow farmers to make timely interventions to prevent the herbicide-escape plants from completing their life cycle and adding to the weed seedbank.

Nomenclature: common chickweed, *Stellaria media* (L.) Vill.

Keywords: Artificial intelligence model, chlorophyll fluorescence, herbicide-resistant weeds, light reflectance values, machine learning, spectral signature.

Introduction

Use of synthetic herbicides to control weeds in agricultural and non-agricultural systems is a common practice in many parts of the world (Gianessi 2013). However, reliance on continuous use of herbicides with the same mode of action to control weeds can lead to rapid evolution of herbicide-resistant weed populations (Ofosu et al. 2023). Recent data shows that the number of unique cases (species x site of action) of herbicide-resistant weeds has significantly increased from zero to about 530 worldwide in just a span of 45 years (Heap 2024).

Globally, farmers lose an estimated $95 billion annually from yield reduction due to uncontrolled weed infestation (ISAAA 2009). Herbicide-resistant weeds may exacerbate this problem (Clay 2021) and further pose a significant threat to crop production and food security (Heap 2014; Lonhienne et al. 2018). Herbicide-resistant weeds require herbicides from an alternative mode of action or more expensive control methods for effective control (Clay 2021), which further increases crop production costs.

Herbicide resistance is becoming a big problem in the San Joaquin Valley of California which is considered the food basket of the world (Shrestha et al. 2010). There are now 161 different unique cases of herbicide resistance observed in the U.S., thirty-two of which are in California (Heap 2024) and these numbers are expected to increase. Most of these cases are of evolved resistance to ALS or 5-enolpyruvylshikimate 3-phosphate (EPSPS) inhibiting herbicides (Dias et al. 2021). The occurrence of acetolactate synthetase inhibitor herbicide resistance in more weed species is continuously rising at an alarming rate posing a greater challenge for weed management, food production, and environmental health (Hanson et al. 2014). Furthermore, documented cases of ALS herbicide resistance in different weed species are significantly higher than for any other class of agricultural herbicides (Heap 2024).

Common chickweed is a broadleaf annual weed species commonly found in agricultural fields infesting wheat (*Triticum aestivum* L.), triticale (x Triticosecale Wittmack), barley (*Hordeum vulgare* L.), oats (*Avena sativa* L.), and several other annual and perennial crops in the Central Valley of California. Overuse and reliance on a single herbicide or a similar mode of action to control common chickweed for extended duration has led to the evolution of herbicide-resistant populations. Over time, the common chickweed has developed resistance to ALS herbicides (Saari et al. 1992). ALS inhibitors are Group 2 herbicides that prevent the ALS enzyme from biosynthesizing the essential branch-chain amino acids (isoleucine, leucine, and valine) thus impairing plants from functioning properly (Whitcomb 1999; Zhou et al. 2007). This is due to mutations in the ALS gene leading to altered herbicide binding sites which make the enzyme less sensitive to inhibition by the herbicide (Heap 2024).

The first resistant common chickweed to three different ALS herbicides in California was reported in 2022, in small grain crop fields (Heap 2024). Target-site resistance (TSR) is the most common type of herbicide resistance in common chickweed and has been reported in all major herbicide classes, including glyphosate, ALS inhibitors, and triazines. Sulfonylurea and imidazolinone herbicides are both linked to target-site resistance in common chickweed (Roberson, 2009). Over the past three decades, resistance to these two ALS herbicides was observed in common chickweed biotypes (Saari et al. 1992). However, it has not been confirmed yet if the ALS-resistant common chickweed has TSR mechanism.

Different approaches have been developed to try to confirm herbicide-resistant weed populations. The standard methods are the use of genetic sequencing (Jones et al. 2023), which detects/confirms a resistant gene or genes in weeds, and/or herbicide dose-response studies (Seefelt et al. 1995). These methods are very accurate but cannot be utilized in the field, are time and labor-intensive, and are very costly. A new technique developed in 2020 was the use of Spectral Weed Indices (SWI) to try to identify glyphosate-resistant weeds. This method uses reflectance values from eight relevant spectral wavelengths specific for weed species to develop the different SWIs (Shirzadifar et al. 2020). In their study, they used discriminative wavebands of 490 nm, 760 nm, 520 nm, 820 nm, 850 nm, 910 nm, 880 nm, and 790 nm to develop the SWI for waterhemp. The results were promising, but the procedure requires the use of a proprietary expensive apparatus – an imaging spectrometer for hyperspectral imaging, labor-intensive pre-processing of data, and very complex calculations. Other techniques include the use of unmanned aerial vehicle (UAV)-acquired thermal and multispectral images to detect the response of weeds. These used ArcGIS for raster and spectral classification to differentiate herbicide-resistant weeds from -susceptible ones (Eide et al. 2021). The study, however, showed that the use of thermal data is not as reliable as the use of the Normalized Difference Vegetation Index (NDVI).

While previous work by Hennessy et al. (2022) has applied convolutional neural network (CNN) to distinguish weeds from regular crops using RGB images, they did not distinguish herbicide-resistant from -susceptible weeds. The use of CNNs to distinguish herbicide-resistant

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

from -susceptible weeds within the same species utilizing full spectrum (UV + visible light + near IR) images acquired through a readily available, converted, low-cost off-the-shelf consumer cameras has never been done. Development of a hyperparameter tuned CNN model for early, quick, and accurate detection and classification of resistant weeds even before observing the visible symptoms of herbicide injury is crucial in making timely interventions and establishing cost-effective environmentally friendly management strategies (Weis & Sökefeld, 2010).

The objective of this study was to develop an AI based herbicide-resistant chickweed classification model that could accurately identify herbicide-resistant weeds expeditiously and more reliably using a low-cost readily available consumer camera, converted to capture full spectrum imagery.

Materials and Methods

Phase 1. Converting a regular camera to capture the full light spectrum.

A camera (Fujifilm X-T200, Fujifilm Corp., 200 Summit Lake Drive, Valhalla, NY, USA) was modified for use in this experiment (Figure 1). All standard photography cameras are equipped with a hot mirror filter that excludes the infrared (IR) and ultraviolet (UV) light spectrum from reaching the sensor. This is essential in producing high quality photographs which cameras are built for. The camera was converted by disassembly and removal of the built-in hot mirror filter to allow the sensor to capture the full light spectrum, including UV, near-IR, and visible light. Aside from the full spectrum images, NDVI, and hot mirror filters were also applied on the modified full spectrum camera to capture NDVI, and regular RGB images.

Phase 2. Obtaining full spectrum images for the development of the herbicide-resistant weed classification model.

This study utilized data from an herbicide-resistance dose response experiment conducted in 2023 and repeated in 2024. In both years of the experiments common chickweed plants were grown in a greenhouse at California State University, Fresno for a suspected ALS herbicide resistance dose response study. The greenhouse temperature and relative humidity was set at 21 °C ± 2°C and 70 %, respectively, with no supplementary lighting. In those studies, there were three populations of suspected ALS-resistant common chickweed plants and a population of confirmed ALS-susceptible chickweed plants grown from seeds collected from an organic pistachio (*Pistacia vera* L.) orchard in the south-Central Valley of California. The common chickweed seeds were planted in plastic trays containing potting soil on 19 February 2023 for the first year and on 15 December 2024 for the second-year trial. Seedlings were transplanted on 13 March and 5 January in 2023 and 2024, respectively in 6.7 cm wide and 8.9 cm deep plastic pots containing an OMRI certified organic garden soil (Kellogg, Carson, CA). The plants were grown till the appropriate stage (approximately 7.5 cm tall with two true leaves) for herbicide treatments. All the plants were treated on 23 March and 30 January in 2023 and 2024, respectively with five different ALS herbicides (imazamox, imazethapyr, mesosulfuron-methyl, pyroxsulam, and tribenuron-methyl), at 0x (control), 0.5x, 1x, 2x, 4x and 8x dosage rates (where x = recommended label rate). The recommended label rates were 10.6 g ai ha^{-1}, 21.3 g ai ha^{-1}, 1.58 g ai ha^{-1}, 14.8 g ai ha^{-1}, and 17.5 g ha^{-1} for imazamox, imazethapyr, mesosulfuron-methyl, pyroxsulam, and tribenuron-methyl, respectively. Both experiments were laid out in a completely randomized design with five replications of each treatment. Each plant in a pot was an experimental unit. The herbicides were applied at a spray volume of 93.5 L ha^{-1} with a CO_2-pressurized backpack sprayer calibrated at a speed of 4.8 km h^{-1} with 0.21 MPa. The sprayer was equipped with Teejet 8002 flat fan nozzles at a spray height of approximately 45 cm above the plants.

High-resolution full-spectrum images of common chickweed plants treated with different ALS herbicides at different dosage rates were obtained using the converted camera in year one and year two. The captured images of herbicide-resistant and -susceptible common chickweed plants grown in the two years were used for the development of an AI based herbicide-resistant weed classification model. Full spectrum, NDVI and RGB images were obtained after the application of the different herbicides. The converted camera was used to capture the full spectrum images. NDVI and hot mirror filters were used to capture NDVI and RGB images. A total of 5,000 full spectrum, NDVI, and RGB (regular photos) images of herbicide-resistant and -susceptible common chickweed plants were obtained at 1, 2, and 3 d after herbicide treatment in both years. After preliminary analysis, full spectrum images captured 3 days after herbicide application were determined to be best suited for the development of an AI based herbicide-resistant weed classification model. The training and validation accuracy of the models developed using full spectrum images obtained 1 and 2 d after herbicide treatments during preliminary analysis were significantly lower compared to those obtained at 3 d. This is likely due to poor detection of any appreciable changes in light reflectance from the slower development of injury symptoms due to ALS inhibitor herbicides. This result is consistent with the study of Shirzadifar et al. (2020), which found the earliest detectable symptoms appeared 3 d after treatment.

Resistant or susceptible classification of common chickweed plants were based on the survival evaluation 28 days after ALS herbicides application. Common chickweed plants that died were classified as susceptible, while plants with any green tissue remaining and growing were classified as ALS-resistant weeds based on visual observation. Results of the completed dose-response study showed that the three common chickweed populations are resistant to ALS herbicides (Herrera et al. 2024).

Phase 3. The development of a superweed classification model using full spectrum images from the converted camera that can classify resistant from susceptible common chickweeds.

Full spectrum straight-out-of-camera (SOOC) JPEG images taken 3 days after herbicide application in both years were classified and separated into two groups– resistant and susceptible common chickweeds, based on final results of the concomitant dose response studies. The images of herbicide-resistant and -susceptible common chickweed plants from both years were uploaded to the program and used to develop an AI classification CNN model (herbicide-resistant classification model).

The herbicide-resistant weed classification model was programmed on Colab (Google, LLC, Mountain View, CA, USA), using Python 3.10, running TensorFlow 2.17 (Google, LLC, Mountain View, CA, USA), with the Keras API. A "Sequential" model with 4 convolutional 2D layers and 10 dense neural net layers was constructed using ADAM as the optimizer, relu, tanh, and sigmoid as the activation functions, and sparse categorical cross entropy loss as the loss function. Metrics that were used in the model were training and validation accuracy, as well as the training and validation loss.

A hyperparameter tuner algorithm was then incorporated into the program to create the best CNN model that could yield optimal accuracy and reliability. An early stopping protocol through best epoch detection was then used to prevent model overfitting.

Full spectrum images of ALS-susceptible and -resistant common chickweed plants were captured using the converted camera. A total of 1500 images of ALS-susceptible and -resistant plants were successfully imported and used by the program to develop and train the herbicide-resistant classification model. The full spectrum photograph displayed in Figure 2 is an example of the successful importation of all the 1,500 images from the data directory. Keras data augmentation was used to improve the training process by rotating and flipping the images before the construction of the CNN model. Figure 3a shows the images in their original orientation while Figure 3b shows the augmented and rotated images arranged on the same orientation. The augmented images were used to construct, train, and validate the CNN model.

The neural network was designed as a sequential algorithm, and it was trained from scratch. Eighty percent (80%) of the total collected images (1,500) was used as a training data set and the remaining 20% was used as the validation data set. The program was deployed, and 10 trials of 100 epochs were completed with the best model being picked by the program based on the validation accuracy. The best performing herbicide-resistant weed classification model was then trained and validated on the entire 1,500 image dataset. A hyperparameter tuning library (KerasTuner) was used to enhance the model's learning process by incorporating optimal hyperparameter combinations to arrive at the best possible herbicide-resistant classification model. An early stopping function was also included to prevent overfitting. The resistant-weed classification model demonstrated superior performance at 36-epochs without overfitting (Figure 4).

Phase 4. Coding the Herbicide-resistant weed Identifier Program (HRIP) which outputs a prediction of ALS-susceptible or -resistant common chickweed.

The HRIP was also programmed on Colab (Google, LLC, Mountain View, CA, USA), using Python 3.10, running TensorFlow 2.17 (Google, LLC, Mountain View, CA, USA), with the Keras API. To check the classifying ability of the newly developed CNN model and its accuracy, twenty-five images of ALS-susceptible and -resistant common chickweed plants were tested in the HRIP utilizing the herbicide-resistant weed classification model. These images of ALS-susceptible and -resistant common chickweed plants used were not included in the original training and validation datasets. The complete step-by-step process used in the identification of ALS-resistant common chickweed plants using the novel full-spectrum imaging and a hyperparameter-tuned CNN (herbicide-resistant classification model) is summarized in Figure 5.

Results and Discussion

The herbicide-resistant classification model with optimal hyperparameter combinations performed best at 36-epochs (Figure 4). It has 4 convolutional 2d layers, 10 dense neural layers, and an output layer. The herbicide-resistant weed classification model has a total of 1,413,506 parameters, all of which are considered trainable. The characteristics and properties of the newly built CNN model are shown in Figure 6.

The training and validation accuracy curves for the superweed classification model exhibited a steady increase over 36 epochs (Figure 7). The set of hyperparameters used in the model rendered a remarkably high training accuracy and at the same time very high validation accuracy indicating that the model was very accurate in differentiating and classifying ALS-susceptible from -resistant common chickweed. In addition, both training loss and validation loss curves for the superweed classification model followed decreasing trends with an optimal gap between them suggesting optimal learning without overfitting. A steadily decreasing trend in the training loss curve suggested that the superweed classification model was improving its learning from the data it was trained on (Figure 7). The very low validation value also showed that the model had achieved "optimal learning". The model performance on the unseen data/images was evaluated using the validation loss. A very low validation loss value achieved in the model indicated that its error on unseen images was very low, and the model was accurate in distinguishing ALS- resistant from - susceptible common chickweed plants.

The HRIP was developed and appended to the newly developed herbicide-resistant weed classification model. Twenty-five ALS-susceptible and -resistant full spectrum images of common chickweed plants that the model had not analyzed before, independent of the 300-image validation set, were used for secondary verification of accuracy using the HRIP running the herbicide resistance classification model. The HRIP was able to independently classify the full spectrum images correctly at 88% accuracy. The performance of HRIP in identifying both herbicide-resistant and -susceptible common chickweed plants were equally high with classification accuracies of 87.5% and 88.24%, respectively (Table 1). An example of a full spectrum image that was accurately identified by the model as "resistant" common chickweed plant is shown in Figure 8. The results of this study were also matched with the actual plant mortality evaluation which corresponded very well (data not shown).

Confusion Matrix for resistant and susceptible chickweed image identification using the HRIP is summarized in Figure 9. It shows that out of 8 images that are resistant, the herbicide-resistant weed classification model predicted that 1 image is susceptible chickweed, and of the 17 susceptible chickweed images, it predicted that 2images were resistant chickweed. The diagonal values indicate the correct predictions by the HRIP while values outside of it are prediction errors.

The development of the herbicide-resistant classification model in this study involved a "train from scratch" approach. This was to ensure that the model would learn effectively from a dataset that had been fully vetted via a completed dose response study (Herrera et al. 2024). With this approach the model eliminated any biases from pre-existing knowledge bases and pre-trained weights, which are commonly encountered when utilizing publicly available image datasets used in "transfer learning" approaches.

The use of the hyperparameter tuner was very helpful in determining the best hyperparameter combinations that led to the development of the best performing herbicide resistance classification model. It enhanced the model's performance and improved its accuracy, precision, and recall (Bartz-Beielstein et al. 2023). Although the determination of hyperparameters can possibly be done manually, it can be a very time-consuming endeavor, and more importantly, it would be uncertain whether the optimal model had been reached with this trial-and-error approach.

The effect of ALS inhibition in susceptible weeds includes disruption of photosynthesis transport and respiration system which leads to chlorophyll degradation (Zhou et al. 2007). Stress or disruption in the transport chain due to the application of ALS herbicide can be detected by measuring changes in the chlorophyll light absorption, reflectance patterns, and chlorophyll fluorescence (Kaiser et al. 2013). All vegetation, including weeds, have distinct light reflectance patterns which can be measured and graphed using a spectrometer (Figure 10). This is called its "spectral signature." Healthy thriving plants have a very different spectral signature when compared to stressed, diseased, or unhealthy plants (Govender et al. 2007). It is this variation in the spectral reflectance between susceptible and resistant weeds when subjected to herbicide treatment, even when very subtle at 72 hours post application, which is exploited by the herbicide resistance classification model to rapidly identify resistant from susceptible strains.

Different weed species have unique spectral signature changes depending on their resistance or susceptibility to herbicides which may fall within or outside the visible light spectrum. Kochia (*Bassia scoparia*) and common waterhemp (*Amaranthus tuberculatus*) weeds' spectral signature discriminative wavebands are in the near infrared (nIR) range (> 750 nm) while those for common ragweed (*Ambrosia artemisiifolia*) are in the visible light wavelength 450–630 nm. (Shirzadifar et al. 2020).

Converted full spectrum camera allows it to capture the subtle differences in the spectral signature of herbicide-treated plants wherever it may be in the light spectrum wavelengths between 300 to 1100 nm (Melentijevic 2015) – which also includes the chlorophyll fluorescence range of 620-750 nm. Chlorophyll fluorescence is the light emitted by the leaves on the red to far-red light (620-750 nm) when exposed to about 400–700 nm (Kalaji et al. 2017). This emitted light can be used as an indicator of a plant's photosynthetic activity and is also useful for the identification of herbicide-resistant weeds (Kaiser et al. 2013). Converting the regular consumer camera to capture full light spectrum (300-1,100 nm) allows the inclusion of all possible areas of differences in spectral signatures, including the chlorophyll fluorescence wavelengths as well as the near IR reflectance values in the full spectrum images of common chickweed. This is the key in the herbicide resistance classification model's accurate differential analysis.

Utilization of full spectrum images to develop the ALS herbicide resistance classification model proved to be more robust and more accurate as compared to using RGB or NDVI images. The validation accuracies of the CNN model developed using full spectrum, NDVI and RGB images were 0.80, 0.53 and 0.65, respectively. Higher training and validation accuracy were observed on CNN model that was trained using full spectrum images compared to the model rendered using NDVI or RGB images. This is likely due to the inclusion of visible light spectrum (380-750 nm) as well as ultraviolet (UV) (<380 nm) and near-infrared (IR) wavelengths (750-1000 nm) in the full spectrum images which reveals subtle differences and details that are invisible to the human eye or even standard camera image sensors (Zhen et al. 2021). While near IR wavelength can show signs of stress in plants even before it becomes visible to the naked eyes as the unhealthy leaf starts to absorb more photons, the visible light spectrum including far-red light can also reveal minute changes in the level of photosynthetic activity (Zhen and van Iersel 2017). RGB wavelength reflectance in plants indicates the amount of red and blue light being absorbed as utilized through photosynthesis and the degree of green light spectrum reflected correlating with the concentration of chlorophyll. As the plant sustains injury and stress from the herbicide, it is unable to absorb as many red and blue light wavelengths. This results in a flattening of the injured plant's spectral signature in the visible light range, as opposed to the usual peaked curve observed in healthy plants with the crest in the green wavelength and troughs in both the red and blue spectra (Figure 10).

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

The ALS herbicide injury symptoms, which include chlorosis, stunting, red leaf veins, and tissue necrosis, are supposed to be evident in 1-4 weeks after herbicide treatment depending on the dosage used and environmental conditions at the time of application (Guo et al. 2015). However, the effect of the ALS herbicides on the common chickweed plants was detected 3 d after herbicide treatment. by HRIP. The model's ability to detect resistant chickweed plants will be consistent for both target site and non-target site resistance, as it was trained using full spectrum images of all resistant plants, regardless of the type of resistance. Herbicide-induced injury symptoms were detected by the program 72 hours after herbicide treatment. This is primarily due to the ability of the converted camera to obtain full spectrum images and capture the spectral signature of common chickweed plants, in varying degrees of ALS injury symptoms, even before they were visible to the naked eye. This study's findings are similar to the observations of Shirzadifar et al. (2020) which established that light reflectance and spectral signature can effectively detect herbicide injury symptoms like chlorosis within 72 hours. In contrast, dose response studies take at least 2 months to be completed and the fastest commercial genetic sequencing analysis can take a minimum of 2 weeks to obtain results. Even newer bulky and expensive chlorophyll fluorescence imaging takes at least 96 hours to detect and classify superweeds after complex and potentially error prone calibration and calculations.

The use of different ALS herbicides and their varying dosage treatments in this research allowed the model to better distinguish herbicide-resistant from herbicide-susceptible plants. This is because the images used to train the model include a wide array or spectrum of injury symptoms from the application of different ALS herbicides and various dosage rates –0.5x - 8x, where x = recommended label rate.

The herbicide group numbering system was developed to help farmers select herbicides belonging to different groups to avoid using the same mode of action repeatedly (Hulme 2022). However, Neve (2007) suggested that the rotation of herbicide modes of action may increase herbicide-resistant weeds because such a practice could select for non-target site resistance mechanisms. Therefore, the problem of herbicide-resistant weeds seems to be an ongoing problem in the future unless non-herbicidal alternative technologies are developed. Hence, any tools that help farmers recognize herbicide-resistant weeds and take proactive measures will be of great benefit and tools such as this HRIP tool may play an important role.

Practical Implications

The results of this study support the research hypothesis that the use of full spectrum images obtained from the modified consumer camera to develop a hyperparameter-tuned CNN model can quickly and accurately classify putative ALS-resistant weeds. It also showed that the herbicide resistance classification model and HRIP developed using the full spectrum JPEG images can quickly and accurately distinguish an ALS -susceptible from a -resistant common chickweed plant.

The HRIP can identify ALS-resistant chickweed plants as early as 72 hours after herbicide application at an impressive accuracy of 88%. It also exhibited robustness, expanding its potential as a valuable tool for real-world and real-time application. It does not require pre-processing of the images or complex calculations to function or operate properly, which is the case in contemporary weed classifiers. The HRIP only needs the straight-out-of-camera (SOOC) JPEG images from the converted full spectrum consumer camera to be able to distinguish ALS-resistant from -susceptible common chickweed plant. Given this simplicity, even farmers inexperienced with this technology will be able to utilize the application with a very low learning curve. It also has broad applicability due to its ability to accurately identify ALS-resistant chickweed plants that were treated with different ALS herbicides, regardless of their chemical group or dosage rate.

Rapid and accurate detection of ALS-resistant weeds using the innovative HRIP can serve as a powerful tool in the fight against the emerging agricultural resistant weed problem in California and around the world. This system can help farmers in establishing more effective and safer weed management practices. It is also anticipated that the technology can be expanded to other weed species such as Palmer amaranth and common water hemp that are resistant to ALS herbicides.

The HRIP running the herbicide resistance classification model can be integrated into a custom-built autonomous ground-based remotely operated vehicle (ROV) or ROVER to detect and dispose of herbicide-resistant weeds in real-time.

Acknowledgments

The authors would like to thank Nicholas Clark of the University of California Cooperative Extension program for the plants grown from locally collected common chickweed seeds.

Funding

This research received no specific grant from any funding agency, commercial or not-for-profit sectors.

Competing Interests

The author(s) declare none.

References

Bartz-Beielstein T, Zaefferer M, Mersmann O (2023) Global Study: Influence of Tuning. Pages 283-301 *in* Zaefferer M, Mersmann O, Bartz-Beielstein T, Bartz E, Eds. Hyperparameter Tuning for Machine and Deep Learning with R, A practical Guide. Singapore: Springer. doi.org/10.1007/978-981-19-5170-1_6

Clay S (2021) Near-term challenges for global agriculture: Herbicide-resistant weeds. Agron J 113: 4463-4472

Dias JL, Clark N, Mathesius K, Light S, Hanson B, Lundy ME, Shrestha A (2021) Poor control of common chickweed with ALS-inhibitor herbicides reported in multiple small grain fields in the southern San Joaquin Valley. Is it a new case of herbicide resistance in California? UC Weed Science Weed Control, Management, Ecology, and Minutia. https://ucanr.edu/blogs/blogcore/postdetail.cfm?postnum=50181. Accessed: December 13, 2023

Eide A, Koparan C, Zhang Y, Ostlie M, Howatt K, Sun X. (2021) UAV-assisted thermal infrared and multispectral imaging of weed canopies for glyphosate resistance detection. Remote Sens 13:4606. https://doi.org/10.3390/rs13224606

Gianessi L. (2013) The increasing importance of herbicides in worldwide crop production. Pest Manage Sci 69:1099-1105

Govender M, Chetty K, Bulcock H (2007) A review of hyperspectral remote sensing and its application in vegetation and water resource studies. Water SA 33:145-151. doi:10.4314/wsa.v33i2.49049

Guo J, Riggins CW, Hausman, NE, Hager AG, Riechers DE, Davis AS, Tranel PJ (2015) Nontarget-site resistance to ALS inhibitors in waterhemp (*Amaranthus tuberculatus*). Weed Sci. 63(2):399-407

Hanson B, Wright S, Sosnoskie L, Fischer A, Jasieniuk M, Roncoroni J, Hembree K, Orloff S, Shrestha A, Al-Khatib K (2014) Maintaining long-term management: Herbicide-resistant weeds challenge some signature cropping systems. Calif Agric 68:142-152. doi: 10.3733/ca.v068n04p142

Heap I (2014) Global perspective of herbicide-resistant weeds. Pest Manage Sci 70:1306-1315

Heap I. (2024) International Herbicide-Resistant Weeds Database. http://www.weedscience.org/Summary/SOADescription.aspx. Accessed May 3, 2024

Hennessy PJ, Esaua TJ, Schumann AW, Zaman QU, Corscadden K W, Farooque AA (2022) Evaluation of cameras and image distance for CNN-based weed detection in wild blueberry. Smart Agric Technol. 1-8. doi:https://doi.org/10.1016/j.atech.2021.100030

Herrera JV, Shrestha A, Waselkov K, Clark NE (2024). Herbicide-resistant common chickweed [*Stellaria media* (L.) Vill.] populations and yield losses in small grain crops in the Central Valley of California [Abstract]. Page 36 *in* Proceedings of The Western Society of Weed Science. Denver, Colorado: Western Society of Weed Science

Hulme PE (2022) Hierarchical cluster analysis of herbicide modes of action reveals distinct classes of multiple resistance in weeds. Pest Manage Sci. 78:1265-1271. doi:10.1002/ps.6744

ISAAA Inc. (2009) FAO: Weeds are Farmers' Enemy Number One. https://www.isaaa.org/kc/cropbiotechupdate/article/default.asp?ID=4580. Accessed May 3, 2024

Jones EAL, Austin R, Dunne JC, Leon RG, Everman WJ (2023) Discrimination between protoporphyrinogen oxidase–inhibiting herbicide-resistant and herbicide-susceptible redroot pigweed (*Amaranthus retroflexus*) with spectral reflectance. Weed Sci 71:198-205 doi:10.1017/wsc.2023.25

Kaiser Y, Menegat A, Gerhards R (2013) Chlorophyll fluorescence imaging: a new method for rapid detection of herbicide resistance in *Alopecurus myosuroides*. Weed Res 53:399-406. doi: 10.1111/wre.12043

Kalaji HM, Schansker G, Brestic M, Bussotti F, Calatayud A, Ferroni L, Goltsev V, Guidi L, Jajoo A, Li P, Losciale P, Mishra V, Misra A, Nebauer S, Pancaldi S, Penella C, Pollastrini M, Suresh K, Tambussi E., Yanniccari M, Zivcak M, Cetner M, Samborska I, Stirbet A, Olsovska K, Kunderlikova K, Shelonzek H, Rusinowski S, Baba W (2017) Frequently asked questions about chlorophyll fluorescence, the sequel. Photosynth Res 132:13-66. doi:DOI 10.1007/s11120-016-0318-y

Lonhienne T, Garcia MD, Pierens G, Mobli M, Nouwens A, Guddat LW (2018) Structural insights into the mechanism of inhibition of AHAS by herbicides. Proc. Natl. Acad. Sci. U.S.A. 115(9):E1945-E1945. https://doi.org/10.1073/pnas.1714392115

Melentijevic I. (2015) The Potential of Full Spectrum Conversion. Retrieved from Kolari. https://kolarivision.com/full_spectrum_conversion/. Accessed May 3, 2024

Neve P (2007) Challenges for herbicide resistance evolution and management: 50 years after Harper. Weed Res 47:365-369

Ofosu R, Agyemang ED, Márton A, Pásztor G, Taller J, Kazinczi G (2023). Herbicide resistance: Managing weeds in a changing world. Agronomy 13:1595 https://doi.org/10.3390/agronomy13061595

Roberson R. (2009) Herbicide resistant common chickweed growing problem. Retrieved from FarmProgress. https://www.farmprogress.com/management/resistant-chickweed-a-growing-problem. Accessed May 3, 2024

Saari LL, Cotterman JC, Smith WF, Primiani MM (1992) Sulfonylurea herbicide resistance in common chickweed, perennial ryegrass, and Russian thistle. Pestic Biochem Physiol 42:110-118

Seefelt SS, Jensen JE, Fuerst EP (1995) Log-logistic analysis of herbicide dose-response relationship. Weed Technol 9:218-227

Shirzadifar A, Bajwa S, Nowatzki J, Shojaeiaranic J (2020) Development of spectral indices for identifying glyphosate-resistant weeds. Comput Electron Agric 170:1-9

Shrestha A, Hanson BD, Fidelibus MW, Alcorta M (2010) Growth, phenology, and intraspecific competition between glyphosate-resistant and glyphosate-susceptible horseweeds (*Conyza canadensis*) in the San Joaquin Valley of California. Weed Sci 58:147–153. doi:10.1614/WS-D-09-00022.1

Weis M, Sökefeld M (2010) Detection and Identification of Weeds. Pages 119-134 in: Oerke, EC., Gerhards, R., Menz, G., Sikora, R, eds. Precision Crop Protection - the Challenge and Use of Heterogeneity. Dordrecht:Springer. https://doi.org/10.1007/978-90-481-9277-9_8

Whitcomb C (1999) An introduction to ALS-inhibiting herbicides. Toxicol. Ind. Health 15(1-2): 232-240. https://doi.org/10.1177/074823379901500120

Zhen S, Iersel MW (2017). Far-red light is needed for efficient photochemistry and photosynthesis. J Plant Physiol 209:115-122 doi:dx.doi.org/10.1016/j.jplph.2016.12.004

Zhen S, Iersel MV, Bugbee B (2021) Why far-red photons should be included in the definition of photosynthetic photons and the measurement of horticultural fixture efficacy. Front Plant Sci 12:1-4. doi:10.3389/fpls.2021.693445

Zhou Q, Liu W, Zhang Y, Liu KK (2007) Action mechanisms of acetolactate synthase-inhibiting herbicides. Pestic Biochem Physiol 89:89-96

Table 1. Discriminative classification of common chickweed plants based on AI Herbicide-Resistant weed Identifier Program (HRIP) running the herbicide-resistant weed classification model.

lassification	Total no. of images tested	Right classification	Wrong classification	Accuracy
Resistant	8	7	1	87.5%
Susceptible	17	15	2	88.3%
Total	25	22	3	88.0%

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

Figure 1. A converted Fujifilm X-T200 camera

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

Figure 2. Program used to successfully import the full spectrum images.

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

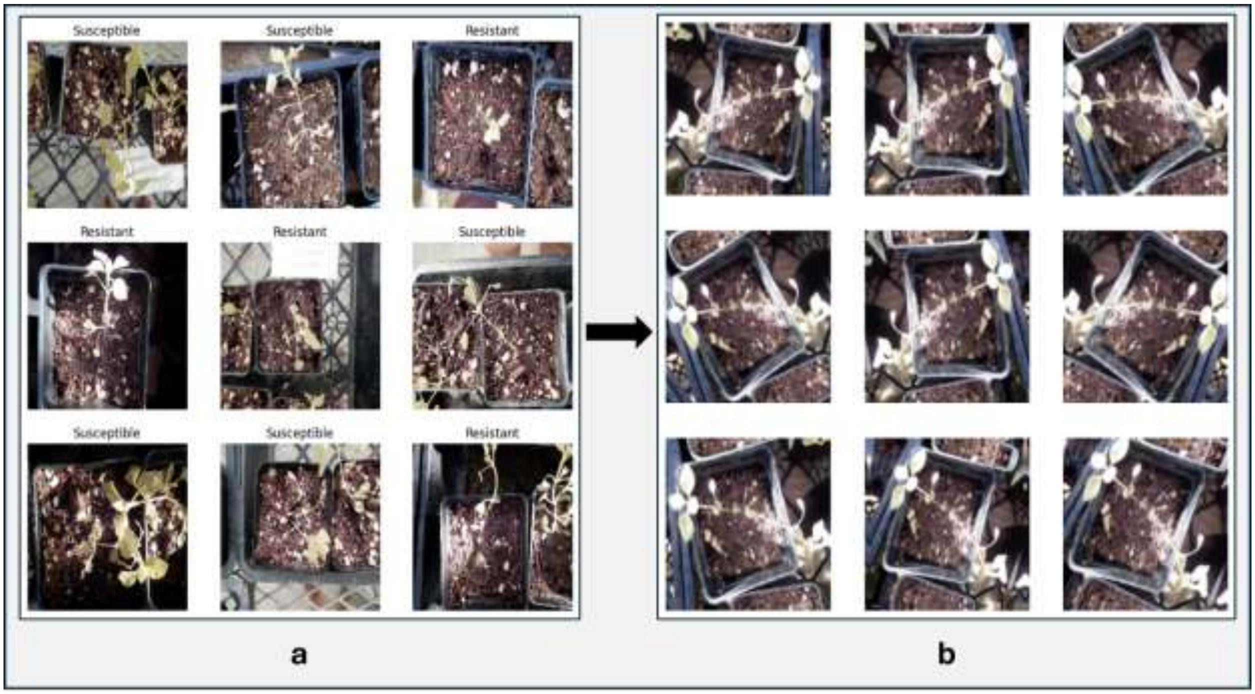

Figure 3. Full spectrum images before Keras data augmentation program was employed (a). Rotated and flipped full spectrum images improved by Keras data augmentation program (b).

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

```
Epoch 22/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.7026 - loss: 0.5476 - val_accuracy: 0.7100 - val_loss: 0.5536
Epoch 23/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.7617 - loss: 0.4970 - val_accuracy: 0.7033 - val_loss: 0.5497
Epoch 24/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.7528 - loss: 0.4955 - val_accuracy: 0.7100 - val_loss: 0.5412
Epoch 25/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.7585 - loss: 0.4999 - val_accuracy: 0.7100 - val_loss: 0.5515
Epoch 26/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7240 - loss: 0.5190 - val_accuracy: 0.6967 - val_loss: 0.5828
Epoch 27/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.7436 - loss: 0.4974 - val_accuracy: 0.7233 - val_loss: 0.5118
Epoch 28/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7555 - loss: 0.4732 - val_accuracy: 0.6833 - val_loss: 0.5678
Epoch 29/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7679 - loss: 0.4792 - val_accuracy: 0.7033 - val_loss: 0.5699
Epoch 30/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.7842 - loss: 0.4573 - val_accuracy: 0.6900 - val_loss: 0.5635
Epoch 31/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7818 - loss: 0.4698 - val_accuracy: 0.6733 - val_loss: 0.5938
Epoch 32/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7759 - loss: 0.4559 - val_accuracy: 0.7100 - val_loss: 0.5445
Epoch 33/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7678 - loss: 0.4489 - val_accuracy: 0.7500 - val_loss: 0.4968
Epoch 34/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7971 - loss: 0.4189 - val_accuracy: 0.6900 - val_loss: 0.5511
Epoch 35/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7678 - loss: 0.4520 - val_accuracy: 0.7233 - val_loss: 0.5218
Epoch 36/50
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.7988 - loss: 0.4224 - val_accuracy: 0.7400 - val_loss: 0.5356
Last epoch: 36
```

Figure 4. Output showing 36 epochs needed to generate the most optimized/best convolutional neural network (CNN) model.

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

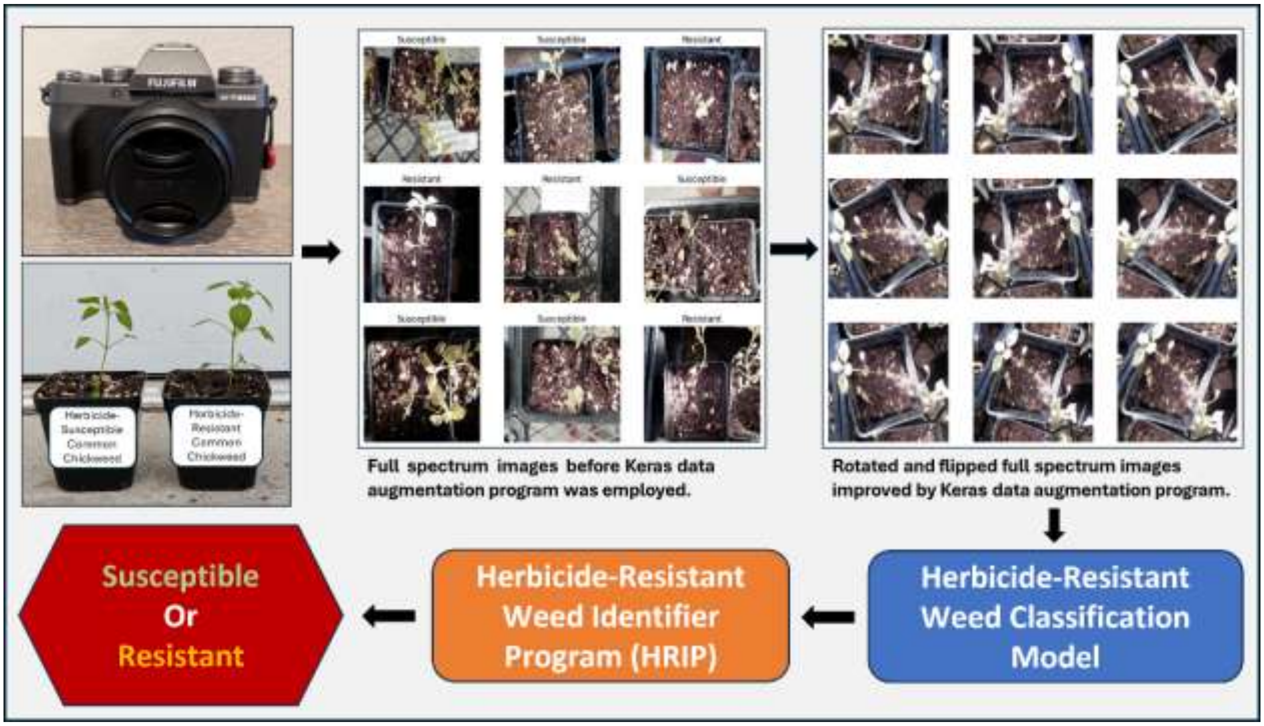

Figure 5. Step-by-Step Identification of Herbicide-Resistant Weeds Using the Herbicide-Resistant Weed Identifier Program (HRIP).

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

Model: "sequential_14"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 180, 180, 3)	0
rescaling_14 (Rescaling)	(None, 180, 180, 3)	0
conv2d_56 (Conv2D)	(None, 178, 178, 112)	3,136
max_pooling2d_56 (MaxPooling2D)	(None, 89, 89, 112)	0
conv2d_57 (Conv2D)	(None, 87, 87, 112)	113,008
max_pooling2d_57 (MaxPooling2D)	(None, 43, 43, 112)	0
conv2d_58 (Conv2D)	(None, 41, 41, 112)	113,008
max_pooling2d_58 (MaxPooling2D)	(None, 20, 20, 112)	0
conv2d_59 (Conv2D)	(None, 18, 18, 112)	113,008
max_pooling2d_59 (MaxPooling2D)	(None, 9, 9, 112)	0
flatten_14 (Flatten)	(None, 9072)	0
dense_140 (Dense)	(None, 112)	1,016,176
dense_141 (Dense)	(None, 16)	1,808
dense_142 (Dense)	(None, 32)	544
dense_143 (Dense)	(None, 32)	1,056
dense_144 (Dense)	(None, 96)	3,168
dense_145 (Dense)	(None, 32)	3,104
dense_146 (Dense)	(None, 112)	3,696
dense_147 (Dense)	(None, 128)	14,464
dense_148 (Dense)	(None, 112)	14,448
dense_149 (Dense)	(None, 112)	12,656
outputs (Dense)	(None, 2)	226

Total params: 1,413,506 (5.39 MB)
Trainable params: 1,413,506 (5.39 MB)
Non-trainable params: 0 (0.00 B)

Figure 6. Output describing the characteristics of the herbicide-resistant weed classification model.

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

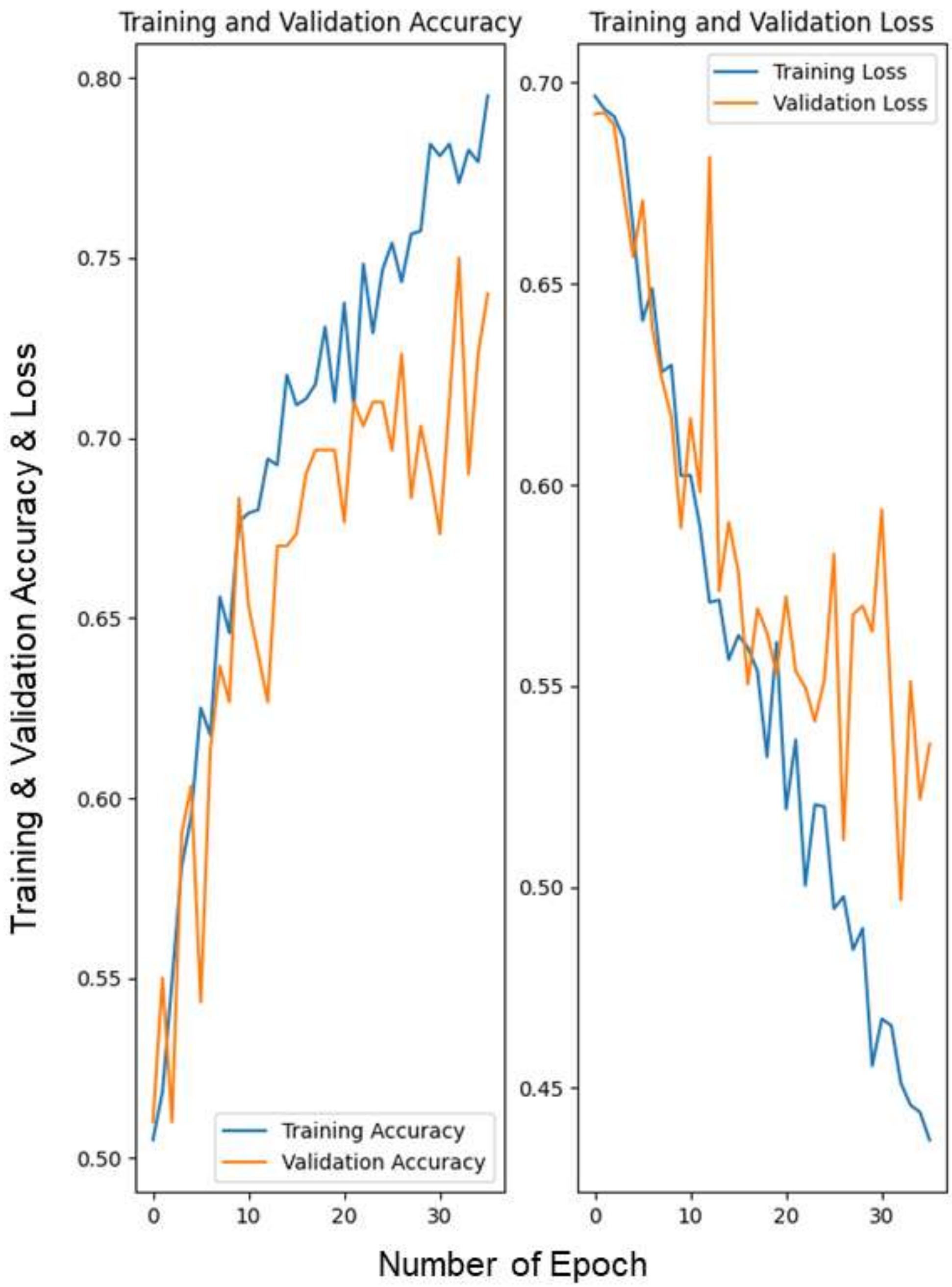

Figure 7. Training & validation loss curves showing steadily decreasing values and the accuracy curves show steadily increasing values with optimal gaps between them indicating optimal learning without overfitting.

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

Figure 8. Herbicide-resistant weed identifier program (HRIP) which outputs weed classification – "Resistant".

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

		Predicted Condition		
	Total (8 + 17)	Resistant 9	Susceptible 16	Accuracy
Actual Condition	Positive 8	True Positive 7	False Negative 1	87.5% 12.5%
	Negative 17	False Positive 2	True Negative 15	88.2% 11.8%

Figure 9. Confusion Matrix showing the performance of herbicide-resistant weed identifier program (HRIP) running the herbicide- resistant classification model. (*Resistant chickweed image is classified positive while susceptible chickweed image is classified negative*).

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press

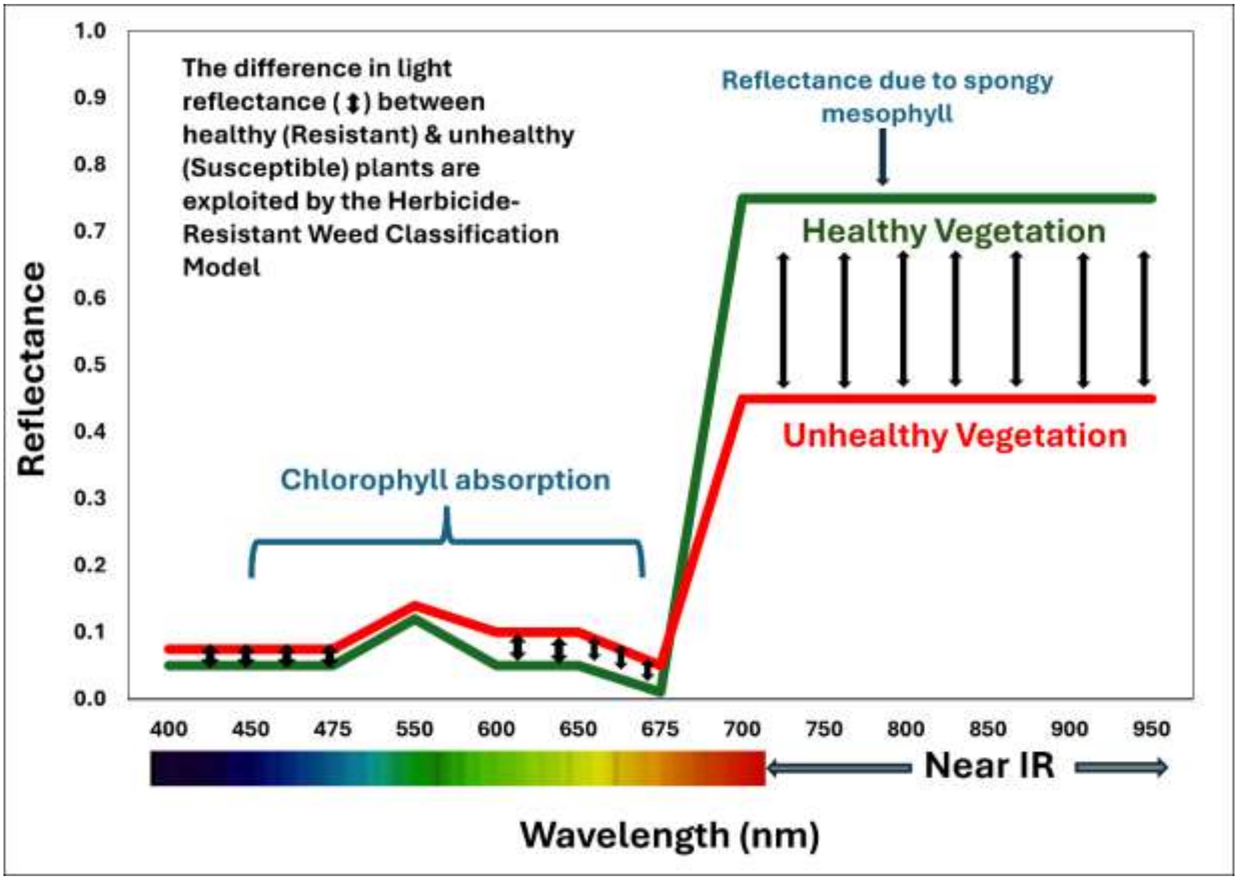

Figure 10. Illustration of comparison of spectral signatures of healthy and unhealthy plants.

https://doi.org/10.1017/wet.2024.109 Published online by Cambridge University Press