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RESEARCH ARTICLE

An Agriprecision Decision Support System for Weed Management in Pastures

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ABSTRACT Pastures are a vital source of dairy products and cattle nutrition, and as such, play a significant role in New Zealand's agricultural economy. However, weeds can be a major problem for pastures, making it a challenge for dairy farmers to monitor and control them. Currently, most of the tasks for weed management are done manually, and farmers lack persistent technology for weed control. This motivated us to design, implement, and evaluate a Decision Support System (DSS) to detect weeds in pastures and provide decisions for the cleanup of weeds. Our proposed system uses two primary inputs: weeds and bare patches. We created a synthetic dataset to train a weed detection model and designed a fuzzy inference system to assess a pasture. We also used a neuro-fuzzy system in our DSS to evaluate our fuzzy model and tune its parameters for better functioning and accuracy. Our work aims to assist dairy farmers in better weed monitoring, as well as to provide 2D maps of weed density and yield score, which can be of significant value when no digital and meaningful images of pastures exist. The system can also support farmers in scheduling, recommending prohibitive tasks, and storing historical data for pasture analysis, collaborated by stakeholders.

INDEX TERMS Fuzzy systems, object detection, pasture management, decision making, decision support systems, fuzzy neural networks.

I. INTRODUCTION

Pastures provide the main source of nutrition for livestock, with grass as the primary food source. Production of grass for cattle significantly impacts several primary industries, including dairy and meat production, and the milk industry. According to New Zealand treasury [24], dairy is contributing up to 18.6 billion dollars to New Zealand economy in 2021 with a 5.3 % GDP and 23 % of total export values. Any dairy farming methodology aims to increase pasture production, considering the many existing problems limiting this goal.

One of the most significant and long-lasting problems in pastures is weeds. They limit grass's space, nutrients, and resources, leading to a loss of revenue and negative impact on dairy production. Although dairy farmers do many tasks to maintain pastures free of weeds, they need a digital tool or software application to monitor, control, and evaluate their pastures. They currently do most weed management tasks manually, using no online and historical information on pastures, and no images, pastoral data, and automatic prohibitive actions assisting them with weed management.

We have discussed in the section II that the existing research on weed management mainly focuses on detecting weeds in crops and not in pastures. Additionally, the majority of these studies only focus on detection and do not provide further data processing or discussion on how to apply them in weed management, which is crucial for a practical application.

In the following, we have cited the studies which could be categorised into two sections:

1) the studies which have extended their data processing after weed detection to produce more informative and practical outputs for farmers

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2) the studies which have integrated their models into other devices or hardware platforms to provide farmers with more functional help in their fields

Our proposed system also considers the variable of bareness of a pasture, as patches of bare spots where neither grass nor weeds are growing can shrink pasture productivity. Sowing grass seeds in these locations will contribute to increasing productivity. We provide both the density of weeds and the bareness to DSS for enhanced productivity of pastures.

It is important to note that while these studies may have promising results, they may not be directly applicable to the specific case of detecting weeds in pastures, as the conditions and variables may be different. Further research and testing would be needed to determine the effectiveness of these methods in the specific context of pasture weed detection.

We can summarise the contributions of our work as follows:

1) Introduction of quantification into the pastoral environment such as weed densities, bare patches, and yield score for weed management and assessment
2) Use of fuzzy sets as an explainable and transparent model in our DSS
3) Assessment and evaluation of our DSS

The paper is organised with a literature review in Section II, methodology in Section III, results in Section IV, limitation in Sections V and conclusion and future work in Section VI.

II. RELATED WORK

A. DECISION SUPPORT SYSTEMS (DSS) FOR PASTURE MANAGEMENT

The advent of sensor technology within the agricultural sector has fostered the development and execution of a multitude of applications. Yet, the specific usage of these sensors within pasture management is an aspect that warrants further investigative research and development.

We have classified our literature review into two categories: in-crop and in-pasture weed detection models. The studies presented below showcase examples of deep learning models used for weed identification in agricultural crop fields.

Nguyen et al. [1] designed an agriprecision application with realistic weed images that were trained by a deep-learning model. The study shows the experiments in three crop environments, and they have explored the prospect of integrating a robot with a camera sensor to enable the detection of weeds. In order to evaluate the efficacy of the proposed system, the authors have presented a set of performance metrics.

Jogi et al. [40] studied in-crop weed identification with a deep learning algorithm. The study focuses on the real-time operations of weed detection to improve latency. They used a spot-wise method to overcome latency issues arising from uniform spraying. Kulkarni et al. [26] studied in-crop weed detection using a Convolutional Neural Network (CNN) to classify weeds in a crop environment. After detection, the final task is sending detection images to farmers' cell phones. López-Granados et al.

Reference [36] examined features of weeds with an object detection algorithm in an in-crop environment. Their algorithm used a small airplane or drone for image collection and specified weed densities as output results. Lottes et al. [37] studied another in-crop environment with a weed detection model trained by a dataset of real images. The research shows training a model on detecting weeds' joint stems instead of weed's leaves or the entire weed. Once they used the model on a spraying robot, they could detect joint stems for better pasture monitoring. Irias Tejeda et al. [38] showed another in-crop study of object detection. Although they noted using their model in an agriprecision application, it is not discussed how and where it can be applied in a system to help farmers.

The following studies demonstrate the weed detection models in in-pasture environments. Chegini et al. Zhang et al. [25] compared the accuracy of machine learning and deep learning algorithms in an in-pasture environment where similar visual characteristics exist between grass and weeds. Reference [42] used the MaskRCNN model to detect California thistle in New Zealand pastures and achieved high accuracy with a synthetic dataset. Elakkiya et al.

The selected studies employed various techniques including object detection algorithms, convolutional neural networks, and joint stem detection models to accurately identify and classify weeds in different environments. The primary objective of these investigations was to develop effective systems that could aid farmers in monitoring and managing weed populations more efficiently. Some studies explored the transmission of detection images to farmers' mobile devices, while others proposed the use of spraying robots equipped with joint stem detection capabilities to enhance pasture monitoring. However, it is important to note that not all studies extensively discussed the practical implementation and impact of these models and systems in assisting farmers.

Jin et al. [2] proposed an innovative approach by combining an object detection model with a genetic algorithm for segmenting images based on color. Their research primarily concentrated on crop fields and employed two distinct models: one for detecting easily identifiable weeds and another for detecting unclear and blurry weed instances. This integration of techniques resulted in improved detection accuracy. However, it is important to note that further discussion is required regarding the integration of the entire model into a practical automated system for real-world applications.

Yu et al. [39] conducted research on a deep learning algorithm trained specifically for three types of weeds. The study demonstrated high performance of their model in detecting and classifying these weeds. However, there is a gap in the discussion regarding the integration and practical utilisation of this algorithm as a component within a comprehensive weed management system. Further exploration is necessary to explore the potential integration of their model

TABLE 1. Key findings of peer-reviewed works on weed detection.

Paper	Model	Discussion on automated system	Environment
[1]	Deep learning	In a robotic system for spraying	Crop
[40]	Deep learning	Not discussed	Crop
[26]	Deep learning	Producing notification for farmers	Crop
[2]	Deep learning and optimisation algorithm	Not discussed	Crop
[37]	Deep learning	In a robotic system for spraying	Crop
[39]	Deep learning	Not discussed	Crop
[38]	Deep learning	In an automated system but not explicitly discussed	Crop
[36]	Deep learning	Weed densities	Desert
[25]	Machine learning and deep learning	Not discussed	Pasture
[41]	Deep learning	Fuzzy inference system	Pasture
Our study	Deep learning and fuzzy inference system	DSS for weed management	Pasture

into real-world applications for effective weed detection and management.

Chegini et al. [41] presented a system that utilizes weed density and bare patches as input to calculate a yield score for pasture areas. The researchers extracted two fuzzy variables from visual data of pastures and integrated them into a Decision Support System (DSS) model.

Table 1 presents a summary of the reviewed papers, categorizing them based on the environmental study they focus on, the employed method or algorithm, and whether they discuss the automation aspect of the system.

Despite the existence of automated Decision Support Systems (DSS) software for various agricultural contexts, such as soil monitoring and animal behaviour, there is still a need for more research and attention in the field of pastures. According to literature on precision agriculture, there is a strong need for software implementation that can effectively process pastoral environments with a high degree of automation. Such software could aid dairy farmers in monitoring and implementing preventative actions, as well as assisting with weed management and destruction.

The DSSs have been designed based on farmers' behaviour and actions. Macé et al. [10] depict a simple behavioural DSS for weed control in three stages:

1) pasture observation
2) choosing proper actions such as spraying or mowing
3) evaluating the pasture

Additionally, incorporating a stage of re-evaluation into the process can make it iterative, continuous, and consistent. The aforementioned stages can serve as key considerations when designing and implementing any DSS model for weed management.

Sønderskov et al. [31] present a DSS that utilises a behavioural model from [10] to recommend the appropriate dose of sprays based on the duration of observation. The model utilises data from the crop environment, but there is no explanation on the specific model used in the DSS. Additionally, the study does not address the practical application of the system in pastures.

Colas et al. [32] conducted a survey among farmers to gain insights on how to design and implement a DSS for weed control. The study focuses on the creation of a decision tree model to present survey data. The survey results indicate that farmers desire a synthetic tool with rule-based decisions for a DSS. The study is considered as a prototype for a DSS, emphasising the need for a practical and functional system among farmers. However, the study only focuses on the crop environment and does not provide any modelling or insight for pastures.

Kanatas et al. [33] evaluated a weed DSS for its accuracy and effectiveness. According to the study, a DSS should provide useful information on fields to aid in management. The DSS should also be designed to be interactive, allowing for validation and improvement of experiments. The paper highlights the use of advanced technology and AI models in DSS to assist farmers in estimating weed growth, assessing yield, and recommending preventative actions. The paper also suggests that a DSS should be able to quantify the level of weeds and evaluate the yield. These suggestions and recommendations from the paper have been applied in practical use in our current study.

Vishwajith et al. [34] developed a DSS that utilises a single computer-aided platform on crop environment to assist farmers in acquiring basic information on soil, water, and weed conditions. However, the study lacks clarity on the specific model used in their DSS, as well as the methods and data processing techniques employed. Additionally, the study only focuses on crops and does not address pasture environments. While the study provides insight on DSS for crop management, we employed a unique methodology for our study in pastures using a coded model that can be validated and tested using pastoral images.

Masin et al. [35] investigated the positive effects of monitoring and recording weed densities in crops. They proposed that incorporating weed densities as useful crop data can enhance the reliability, precision, and accuracy of a DSS. Their DSS model aims to estimate the impact of environmental factors such as temperature, rainfall, and soil temperature on weed growth. However, the study solely focuses on crops and does not mention pastures. Similarly to other studies, we employed an in-pasture analysis of weed densities in our DSS.

When it comes to DSS, it is important for farmers and dairy farmers to have easy-to-use and transparent systems. One reason why dairy farmers may not be inclined to use software platforms and technologies for weed management is that they can be complex and lack transparency in their internal operations for data processing. This motivated us to use a fuzzy inference system for data processing.

Fuzzy sets and fuzzy inference systems are useful models for handling real systems and environments. They follow human linguistics and provide transparency in data processing and internal operations, in contrast to Neural Networks (NN). Some studies have employed fuzzy systems and fuzzy sets in their DSS.

S. Sivamani et al. [16] utilised a fuzzy system for animal control. The system takes two inputs of age and weight, and provides four outputs of change-diet, change-diet schedule, need health check-up, and be-ready-for-a-sale. The fuzzy inference system suggests actions for the farmers based on two fuzzy membership functions. For example, the output of change-diet would indicate that the farmers should change the animals' diets.

Nguyen-Anh and Le-Trung [17] address the problem of adaptive programming in an IoT environment, using a fuzzy inference system for controlling complex contexts. Khanum et al. [18] applied a fuzzy system for understanding the conditions of leaves and detecting fungal diseases, using five inputs.

Pandey et al. [19] designed a fuzzy system for agricultural data processing, using crop input data for disease detection to aid decision-making on sprays. They used two inputs, wind and temperature. These examples demonstrate the various ways fuzzy systems can be employed for different agricultural problems to aid farmers in improving the accuracy and timing of routine crop, stock and pasture management tasks. Few studies on modelling agricultural environments with fuzzy systems motivated us to use fuzzy inference systems in our DSS.

Table 2 summarises the studies on fuzzy inference systems in agriculture. The papers presented in this section demonstrate how fuzzy systems can be used for agricultural analysis. As they are efficient in data processing, we employed fuzzy systems in our DSS for processing pastoral images. These studies typically produce outputs that can aid farmers in decision-making, whether through classifying tasks or recommending the best course of action.

Table 3 summarises the key findings and directions from our literature review. We found that a DSS that produces weed density and yield scores is highly desired by dairy farmers. We also incorporated a fuzzy inference system and added a quantification module to convert visual data into variables of weed density and bare patch, which was recommended by our review of DSS papers. Our study context is pasture, which has not been extensively studied in the reviewed papers. After the design and implementation of our DSS, we also applied an Adaptive Neuro-Fuzzy Inference System to evaluate and adjust the internal parameters of the DSS, resulting in a more accurate and functional system.

B. WEED DETECTION MODELS FOR PASTURE MONITORING

Our DSS and fuzzy inference system work with visual data produced by our object detection model. We have used the Mask Region Convolutional Neural Network (MaskRCNN) to process pastoral images and detect weeds. MaskRCNN is a state-of-the-art model in object detection. There are studies that have used object detection models in agricultural applications.

Thanh V. Le et al. [1] employed a FasterRCNN model trained with realistic weed images for improved latency in testing mode. Jin et al. [2] used Mobile net, VGG, and a CNN model with 15000 training images for feature extraction of weeds and detecting 10 weed types in crops. Abdulsalam et al. [4] used You Only Look Once (YOLO) and a ResNet model for classifying four types of weeds. However, these studies focus on weed detection in crop environments and do not discuss their application in pastures.

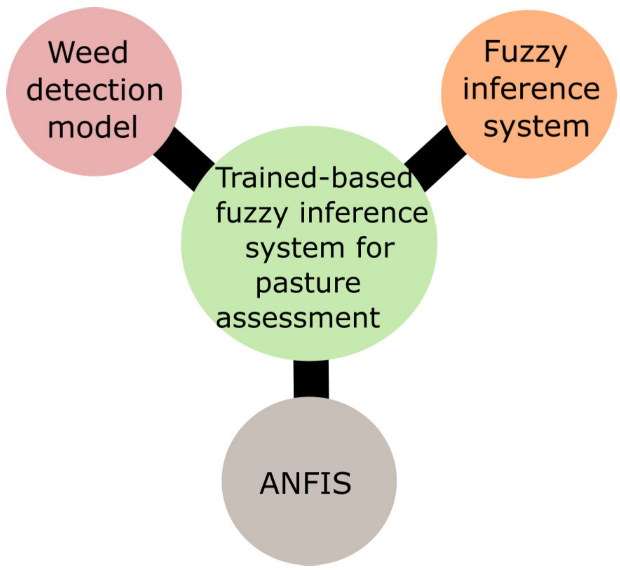

FIGURE 1. Three main components of our literature review in our system design and implementation.

Figure 1 illustrates the three main components of the literature that we studied for designing and implementing our DSS. These are fuzzy inference systems, weed detection models, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The combination of these research components influenced our concept of having a fuzzy inference system that can be trained and enhanced by image output.

III. THE PROPOSED DSS WEED MANAGEMENT SYSTEM

This section describes the design and implementation of our DSS weed management system and its components. Our DSS consists of three main components:

TABLE 2. Examples of fuzzy inference systems on agricultural applications.

Paper	Input	Output)	Purpose
[16]	Two inputs	Four outputs	Animals' checkup and schedule based on their age and weight
[18]	Five inputs	Leaves fungi	Processing leaves conditions for a disease classification
[19]	Two inputs	Spray scheduling	Recommending a spray time based on processing wind and temperature
Our study	Two inputs	Yield score	Processing weed density and bareness and recommending the best time for prohibitive actions against weeds

TABLE 3. Key findings of reviewed papers on DSS.

Paper	Findings	Recommendations (Research gaps)
[10]	A response and reaction approach for DSS in agriculture	Defining systems and models based on observe and react approach
[31]	A study based on observe and react	No pasture
[32]	A prototype of DSS	A functional and practical DSS desired by farmers
[33]	Appreciation of accuracy and assessment in weed management DSS	Quantification, yield scoring, advanced technologies and AI
[34]	A multi-task application for farming	No details on models
[35]	Weed growth and distribution based on environmental variables	Use of weed density in a DSS, no discussion on pasture environment
[16],[17],[18],[19]	Different fuzzy inference systems in agriculture	Not an application of applied fuzzy system in pastures
[1]	Improving weed detection	No pasture
[2]	Detection of 10 weeds	No synthetic dataset
[4]	Weed classification	No pasture

1) MaskRCNN model capable of receiving pastoral dataset images and training for weed detection
2) Fuzzy inference system for processing weed density and bareness
3) A Neuro-Fuzzy system called ANFIS for evaluating the DSS

We considered the importance of weed information obtained from images in decision-making. As our survey study revealed that seeding can help control weed invasion and growth, we defined a second model based on empty areas of a pasture to identify bareness in pastures.

We utilised a fuzzy inference system to process the output of the MaskRCNN model. Figure 2 illustrates our DSS design and implementation flowchart. The weed detection component includes the stages of image preparation, synthetic dataset creation, and model training. The next component, below the weed detection model, is a fuzzy system, which includes a fuzzy inference system for 2D map creation and yield score calculation. An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a component that improves the system.

For the first component, we created two synthetic datasets for weed and bare patch detection. We then developed a weed detection model and trained it with these datasets. The accuracy of the model was enhanced by fine-tuning its hyperparameters. We then stored the masks and image outputs in an array. The quantification component converts the weed output masks into clear ratios and links the weed detection software to a fuzzy inference system. The fuzzy inference system receives the weed and bareness values and evaluates the pasture.

A. MASKRCNN

To detect weeds from images captured in the field, our system employs MaskRCNN. As an enhancement of FasterRCNN, which was used for object detection such as weeds, MaskRCNN generates masks of detected objects. These masks are used to calculate the density of weeds.

The model processes pastoral images as input and detects the weeds and bare spaces. A synthetic dataset was used to train the models. The steps for creating a synthetic dataset are as follows:

1) object extraction from pastoral images
2) background creation by erasing weeds from the images
3) setting up the maximum number of weeds in every image
4) setting up the image resolution
5) defining the required weed orientation such as transformation, rotation, and scale
6) setting up many images
7) attaching weed objects to the background

After creating the synthetic dataset, the object detection model can be trained. Figure 4 illustrates a schematic process of creating our synthetic dataset. We extracted weed and bare patch objects from the images in the first step. Then, we transformed and placed them in the background images. We repeated this process for the number of images required for our synthetic dataset.

A few examples of the MaskRCNN model are shown in Figure 3. The images were collected in the field under various conditions for different types of weeds. Despite the variety of weed types and growth patterns, the model was able to accurately and reliably detect the density of weeds.

Figure 5 displays the detected weeds and empty spaces by our model. The top image shows two weeds in the middle and several scattered empty spots. The bottom images depict the detected weeds and empty spots in colorful masks.

Once the model was trained, we proceeded to carefully select the critical hyperparameters that would significantly influence the accuracy of the model. In this experiment, we fine-tuned a dependable range for each hyperparameter and trained the model multiple times, considering various values within those ranges. The following hyperparameters were specifically chosen for this section:

1) learning rate
2) RoI

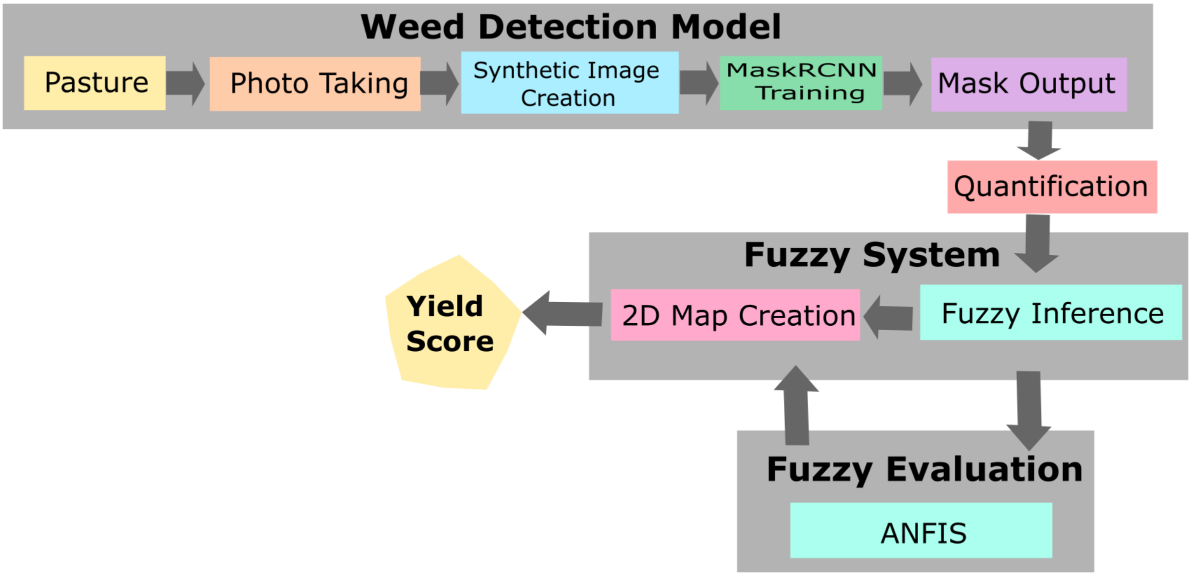

FIGURE 2. Flowchart of our DSS: weed detection, quantification, fuzzy inference, and fuzzy evaluation.

TABLE 4. Precision, Recall, and F1 score values for weed and empty models.

Model	Training Images	Epochs	mAP	Precision	Recall	F1Score
Thistle	500	200*100	0.856	0.72	0.52	0.61
Empty	500	200*100	0.75	0.7	0.6	0.64
Thistle	2500	200*100	0.93	0.78	0.61	0.7
Empty	2500	200*100	0.84	0.74	0.62	0.7

3) Maximum instance
4) RESNET backbone

Epochs and image resolutions were two main training parameters studied in-depth. The study revealed that the scale of 640 X 480 had the best accuracy. Table 4 presents the final results of our experiments on the number of images and epochs in the training set. Precision, recall, and F1-score are the evaluation metrics in our study.

B. QUANTIFICATION

This section describes the module that we have designed and coded to calculate the ratio of weeds and bareness in an image based on the number of detected weeds and bare patches. We calculate the ratio by using the number of output masks and their areas. For example, an array with the shape of (480, 640, 7) represents the detection of seven weeds. The output masks of weeds have a value of 1.

$$T_{weeds} = if \sum_{i=1}^{\#weeds} r[640, 480, i] > 0 \tag{1}$$

$$T_{bareness} = if \sum_{i=1}^{\#empty} r[640, 480, i] > 0 \tag{2}$$

$$Weed\ ratio = \frac{Total\ weed\ pixels}{Total\ image\ pixels} = \frac{\sum T_{weeds}}{640 * 480} \tag{3}$$

$$Bare\ patch\ ratio = \frac{Total\ bare\ pixels}{Total\ image\ pixels} = \frac{\sum T_{bare\ patch}}{640 * 480} \tag{4}$$

We have two approaches for the quantification process:

- Calculating from bounding box
- Calculating from mask

Equations 1-4 depict the quantification stages for calculating the weed-to-grass ratio and the bareness-to-grass ratio. Equation 1 calculates the area of detected weeds, and equation 2 calculates the area of detected bareness. Equation 3 calculates the weed-to-grass ratio, and equation 4 calculates the bareness-to-grass ratio. The results are two scalars, which are used as crisp input for the fuzzy inference system.

C. FUZZY INFERENCE SYSTEM

This section illustrates the design and implementation of our fuzzy inference system. Fuzzy systems are particularly useful for measuring the complexity and uncertainty of a process by defining linguistic variables and fuzzy rules, as discussed in [11] and [12]. The following reasons summarise why a fuzzy inference system is powerful for modelling complex and uncertain processes:

1) Fuzzy systems are best to manage uncertainties in an environment.
2) Fuzzy systems are explainable.
3) Fuzzy rules are flexible and can be adjusted according to process changes.
4) Fuzzy systems are one of the best models for decision making.

We constructed our fuzzy logic model with two variables: weed density and bareness. We then defined our fuzzy rules based on different combinations of variable conditions. The following are the three stages of a fuzzy inference system:

1) Fuzzification: converting crisp values of weed density and bareness into fuzzy membership functions
2) Fuzzy rules' excitement: execution of fuzzy rules to drive a fuzzy output

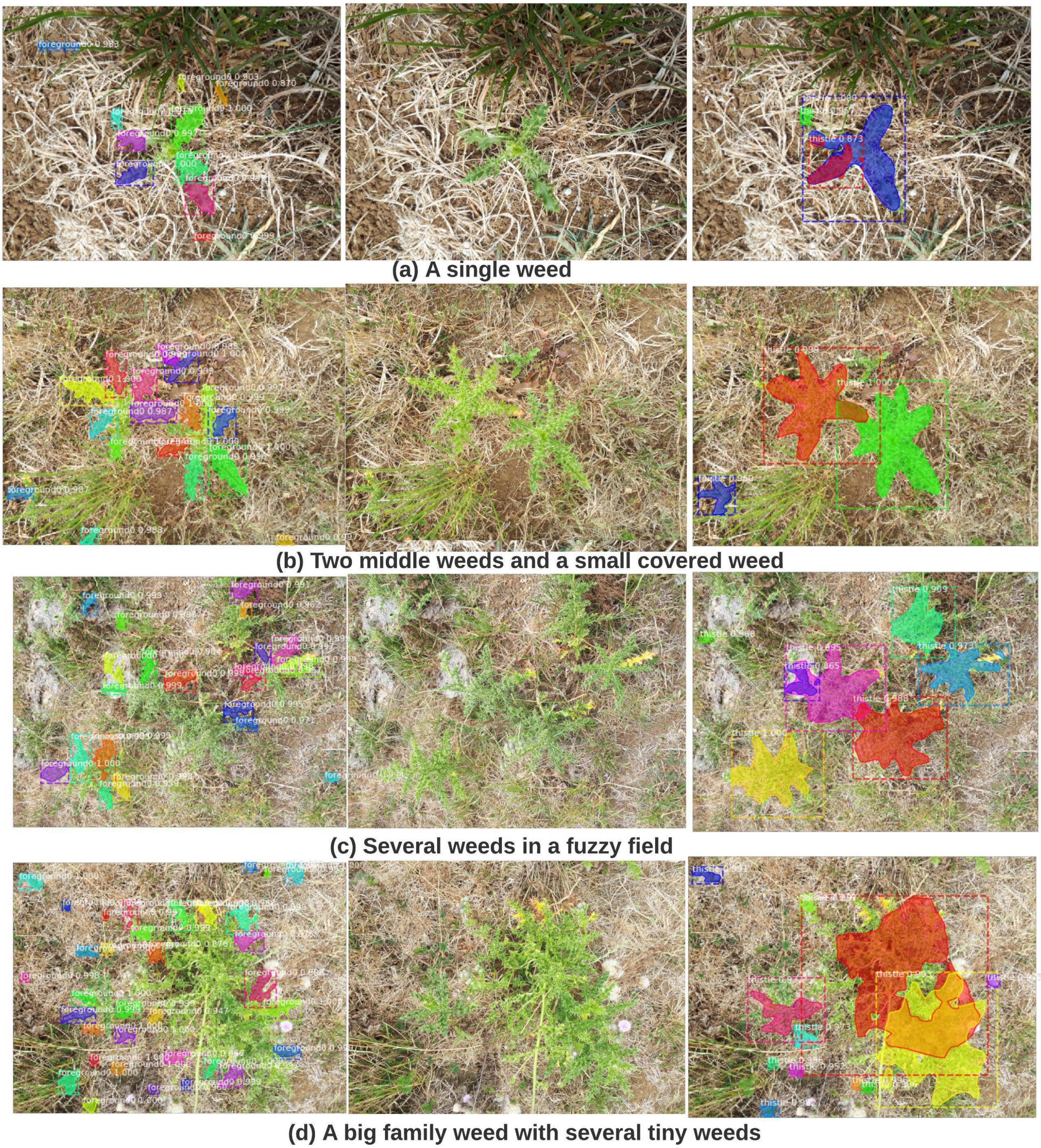

FIGURE 3. The MaskRCNN output on several images.

3) Defuzzification: Converting fuzzy output into crisp values

1) FUZZY VARIABLES

A fuzzy variable, also known as a linguistic variable, is a function that represents the membership of a variable to a certain phenomenon. It ranges from 0 to 1, with 0 indicating minimal membership and 1 indicating maximum membership. Before using any fuzzy system, the input must be converted into a fuzzy variable. For example, a fuzzy variable might describe a car's speed with measurements such as fast, slow, and medium, instead of using exact numerical values (km/h).

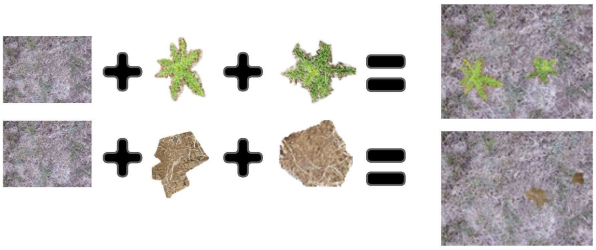

FIGURE 4. The schematic diagram of synthetic creation.

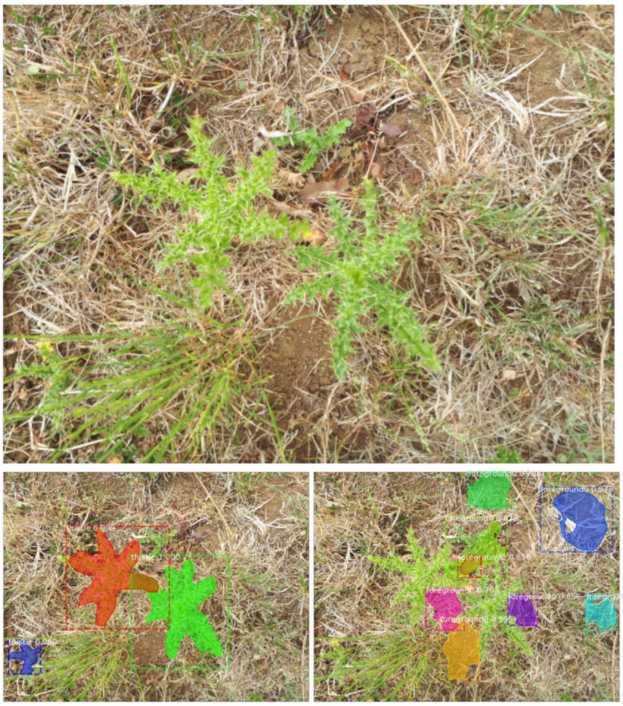

FIGURE 5. MaskRCNN model's output on detecting weeds (left-bottom) and detecting empty spaces (right-bottom).

Therefore, in the first stage, we need to convert crisp data into linguistic variables that can be understood by a fuzzy system.

In a fuzzy system, several types of fuzzy membership functions or fuzzy linguistic variables can be defined and designed for a particular problem. The triangular function is the most common type used. Other types include trapezoidal, gaussian, pending, linear, and bell.

For our decision support system (DSS), we designed and coded two fuzzy variables: weed density and bareness. We categorised each with three fuzzy functions: low density, medium density, and high density for weed density, and three fuzzy functions for bare patches.

For the fuzzy output variable, we defined a variable to show pasture productivity with a qualifying degree, named the yield score, and categorised it into five conditions, each represented by a fuzzy triangular function: excellent yield, good yield, average yield, poor yield, and very poor yield.

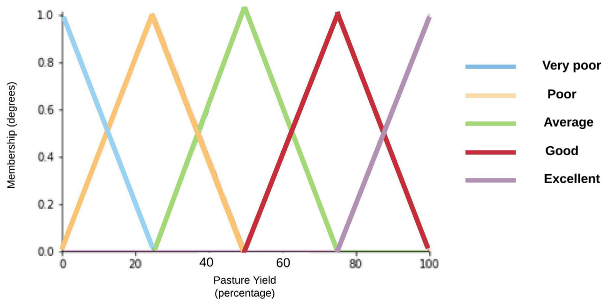

FIGURE 6. Five fuzzy membership functions for pasture productivity.

2) FUZZY RULES AND SURVEY DATA

Fuzzy rules are the core of a fuzzy inference system and are used for reasoning. They process the fuzzy inputs and produce the output as fuzzy membership functions. They are written in the form of "if-then" statements. The rules can also be more complex, such as "if input1 and input2 then."

There are two types of fuzzy output systems: Mamdani and Takagi, Sugeno, and Kang (TSK) [13]. The Mamdani fuzzy system uses a fuzzy membership function for its output, while the TSK fuzzy system uses a linear proposition to represent the fuzzy output. In our study, we used the Mamdani type for our fuzzy inference system.

Equation 5 shows the fundamental Mamdani formula in a fuzzy inference system. Equation 6 shows the same formula for adjusting the fuzzy membership and rule numbers. The dividend of the equation has an outer sigma, which sums up the output of the nine rules we have defined in our fuzzy inference system. Each proposition in the sigma contains a y and internal production of two inputs. The production calculates the membership functions μ, of weed density and bareness of each rule. x is a quantised value of weed density and bareness. In each proposition, the membership function of x is multiplied by y inverse, which results from the output of each rule. In the divisor, there is no y inverse, and the final yield score is achieved after the dividing operation.

We needed $3 \times 3{=}9$ rules to define all the conditions based on our fuzzy rules, as we had two input variables (weed density and bareness) each with three conditions.

Table 5 shows the fuzzy rules of our decision support system (DSS). Each rule checks a condition of weed density and bareness, leading to an Adaptive Network-based Fuzzy Inference System (ANFIS) calculation to determine the yield score. If more conditions and situations of the pasture need to be considered, for example by adding more inputs, they should be included in the fuzzy rules.

Figure 6 displays the five membership functions representing different quality states of a typical pasture, ranging from "very poor" to "excellent."

$$Yield\ score = \frac{\sum_{l=1}^{\#Rules} y^{-1} \prod_{i=1}^{\#Inputs} \mu_i^l(x_i)}{\sum_{l=1}^{\#Rules} \prod_{i=1}^{\#Inputs} \mu_i^l(x_i)} \tag{5}$$

$$Yield\ score = \frac{\sum_{l=1}^{\#9} y^{-1} \prod_{i=1}^{\#2} \mu_i^l(x_i)}{\sum_{l=1}^{\#9} \prod_{i=1}^{\#2} \mu_i^l(x_i)} \tag{6}$$

We can extend the fuzzy rules by adding more inputs, such as wind, humidity, and temperature. Following is an example of a rule that includes the new inputs and their conditions:

if(weed growth is high) and if(temperature is low) and
if(wind is becoming high) and if(bareness is low) and
if(weed density is high) and if(tiny weeds are above 35%)
then (very low score) and (need a high amount of spray)

3) FUZZY OUTPUT

Fuzzy outputs are the third and final part of a fuzzy inference system. They represent the result of data processing and rule handling in a fuzzy inference system. In our case, as we had used the Mamdani system, we chose a triangular membership function for our fuzzy output.

Figure 7 illustrates the network diagram of our fuzzy system, which assesses a pasture. It showcases the flow of data from the fuzzy inputs to the nine fuzzy rules and their integration to generate the fuzzy output.

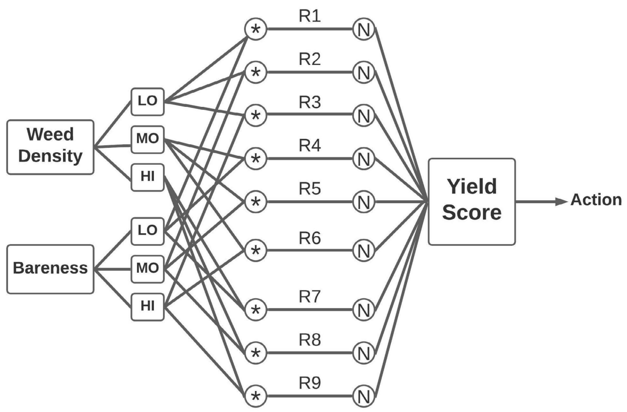

FIGURE 7. **Our fuzzy network for yield scoring based on weed density and pastoral bareness.**

IV. WEED KNOWLEDGE: PASTURE ASSESSMENT

This section explains how we implemented the fuzzy inference system to produce the desired output. We used the python packages of skfuzzy and skfuzzy control for coding and implementation. After designing and implementing the system, we then used Adaptive Network-based Fuzzy Inference System (ANFIS) to process the fuzzy output and membership functions for system enhancement and evaluation. We also proposed a Graphical User Interface (GUI) to display the fundamental parameters and results. A subsection is included to discuss how the system could be used for predicting the yield scores. Figure 8 shows the five pastoral images used for our experiments. Table 6 shows the results of scoring on each image, which is presented in Figure 8. Figure 9 shows a simulation of a land, with the colorful maps showing the density of membership functions and the output of the yield score. The produced score for the studied land is 84.27.

A. FUZZY INFERENCE SYSTEM ENHANCEMENT

This section presents the experiments on our fuzzy inference system to evaluate its accuracy in predicting yield scores. We set up our fuzzy structure in the Matrix Laboratory (MATLAB) software and designed and implemented an Adaptive Network-based Fuzzy Inference System (ANFIS) to train our pastoral data for yield score predictions.

ANFIS is a combination of a neural network model and a fuzzy system. The neural components are used to train the membership functions of the fuzzy system to reach the desired level of accuracy. It has been used in various control systems. By training our fuzzy inference system, we can obtain metrics for evaluating the accuracy of yield score assessment. In this case, we used paired pastoral data points as training data, consisting of weed density and bareness as inputs and yield scores as output. Therefore, our training dataset for ANFIS had two inputs and one output, a total of three columns. The training process allows us to evaluate our fuzzy inference system and improve its accuracy by making adjustments.

$$RMSE = \sqrt{\frac{1}{Data}\sum_{i=0}^{Data}(y((x_i) - y_0(x_i))} \quad (7)$$

We have used the Root Mean Squared Error (RMSE) as our metric to evaluate these experiments. (Equation 7). y is the yield score, and "y_0" is the ANFIS output. *Data* represents the number of yield Scores collected over time as fuzzy score outputs.

We examine two cases of our system: static and dynamic fuzzy systems. In the static fuzzy system, the parameters of the membership functions (such as means and deviations) are fixed and cannot be trained. In contrast, the dynamic fuzzy system has the capability to train and adjust these parameters based on the input data. We have used 100 data points as the training dataset and set up 100 epochs for training. Figure 10 shows the errors of static and dynamic fuzzy systems while trained with 100 epochs. The DSS without training and with no parameter enhancement has an error of 0.25 as the red dot in Figure 10.

In the next stage, we performed hyperparameter tuning to improve the accuracy of our Adaptive Network-based Fuzzy Inference System (ANFIS). The number of membership functions and the type of membership functions are two main parameters that are crucial for the fuzzy model's accuracy and performance. To find the best value of fuzzy membership functions, we changed the configuration of our ANFIS model, trained it and observed the accuracy. To experiment with the shape or type of membership functions, we considered four main types of membership functions. After configuring the ANFIS with each type, we trained our model and recorded the accuracy.

Figure 11 shows the changes in RMSE metric based on increasing numbers of the two mentioned parameters. The best values of accuracy are in the centre of the radar plot. As values close to the centre of the most internal circle

TABLE 5. Fuzzy rules of our weed system framework.

Rule No.	Rule
1	*IF (weed density (WD) is low) and (barrenness (BR) is low) THEN Yield is excellent*
2	*IF (WD is moderate) and (BR is low) THEN Yield is excellent*
3	*IF (WD is high) and (BR is low) THEN Yield is good*
4	*IF (WD is low) and (BR is moderate) THEN Yield is good*
5	*IF (WD is moderate) and (BR is moderate) THEN Yield is average*
6	*IF (WD is high) and (BR is moderate) THEN Yield is poor*
7	*IF (WD is low) and (BR is high) THEN Yield is poor*
8	*IF (WD is moderate) and (BR is high) THEN Yield is very poor*
9	*IF (WD is high) and (BR is high) THEN Yield is very poor*

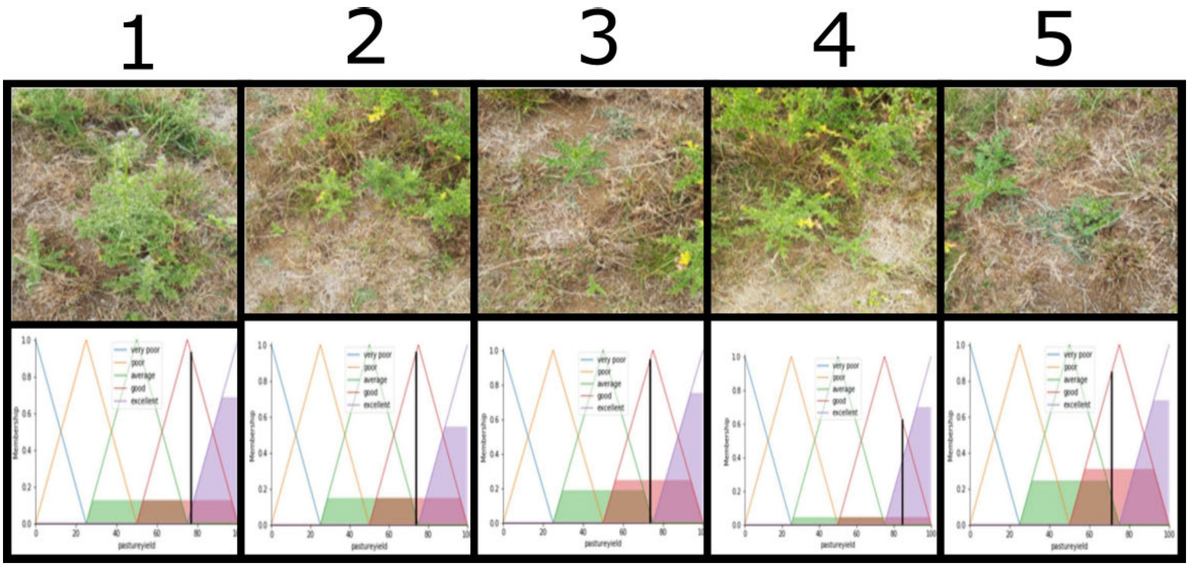

FIGURE 8. Five sample images of our examined pasture with their fuzzy output.

represent the best experimentation, the bell-shape of the membership function and ten membership functions would have the best accuracy. In other words, using ten membership functions with a bell shape will result in the best accuracy of our ANFIS model.

Algorithm 1 shows the sequence of pastoral image processing. The first step is to train a weed detection model using several pastoral images. Next, we quantify the images by producing crisp numbers representing weed density and bareness. These crisp numbers are the input data for the fuzzy inference system. The rules and defuzzification components then produce the yield score. We then use an Adaptive Network-based Fuzzy Inference System (ANFIS) model to train fuzzy membership parameters. We conduct our training and record the Root Mean Squared Error (RMSE), our evaluation metric, according to different parameters and configurations.

In this section we tried to illustrate a prototype for the proposed DSS model for pasture forecasting. The fuzzy inference system can produce yield scores on a specific date and time. Collecting yield scores at different time intervals can lead to a time series of yield scores. Having historical data on a pasture in the form of a time series can help dairy farmers predict their pasture yield. This way, they can have a better insight into the productivity of their pastures and organize their tasks in a proactive manner rather than a reactive one.

Figure 12 illustrates the process of sequencing the three variables: weed density, bareness, and yield score. Each variable can represent a recording point of a time series, suitable for any predictive forecasting model. Incorporating the forecasting values into the yield score of the fuzzy inference system can enhance the decision support system (DSS) for better and more accurate services for dairy farmers.

B. A COMPARISON TO SEGMENT ANYTHING MODEL (SAM)

When it comes to the functionalities of MaskRCNN and SAM, both operate on pixel-wise images and generate masks for the objects they can recognize within an image. However, there is a significant distinction between the two. MaskRCNN is trained by targeting a specific object within an image, whereas SAM can detect any object present in an image.

Another key difference is the size of their trained models. MaskRCNN's model size is 200MB, while SAM's is approximately 2.5GB, which could potentially cause latency

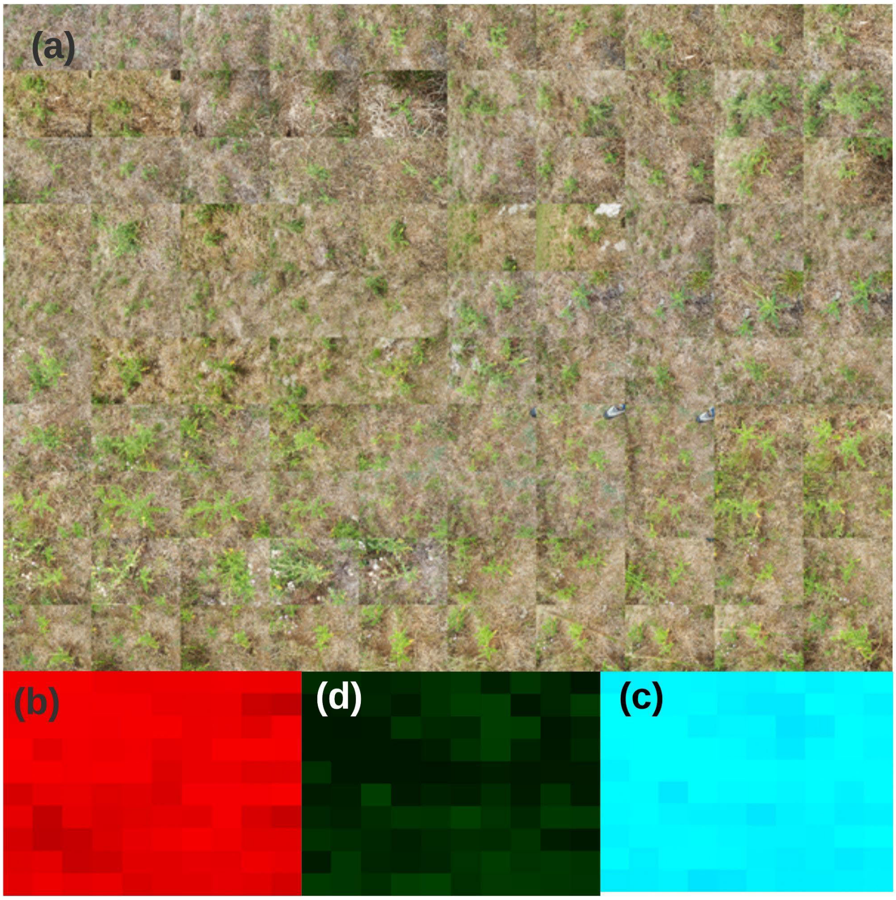

FIGURE 9. The produced 2D maps of our weed system framework. (a) shows a pasture divided into 100 individual images. (b) shows the 2D map of weed density. (c) shows the bareness 2D map, and (d) shows the 2D map of the yield score. For this studied pasture, the yield score is 84.27.

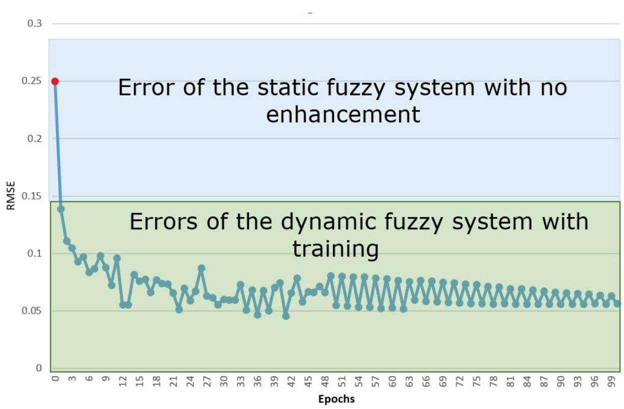

FIGURE 10. The errors of our static fuzzy system with no training (upper section) and with training (lower section).

TABLE 6. Fuzzy rules of our weed system framework.

Figure 8 images	Weed density	bare patch density	Yield score
1	0.3432	0.0635	76.83
2	0.2273	0.0747	73.89
3	0.0947	0.1238	73.50
4	0.3496	0.0224	84.40
5	0.1227	0.1548	71.16

issues during model transfer and deployment in real-world applications.

The training time of MaskrRCNN is much lower than SAM. This is also true about the inference time. For high resolution images a RAM crash message may be received. For inference time, images were scaled to different resolutions all in 3:4 ratio and the inference time was recorded. Figure 13 shows a snapshot of the image scales in various resolutions.

Figure 14 shows the inference time of the same image with different resolutions and scales. The analysis shows how costly it is to detect objects on a high-resolution image with more than 4 minutes as compared to a small resolution image which takes less than a minute. With this experiment, for a practical application the resolution analysis is a crucial stage which should determine the best image scale in the inference time.

For the SAM analysis we demonstrate the impact of Union over Intersection (UoI) on the number of detected masks.

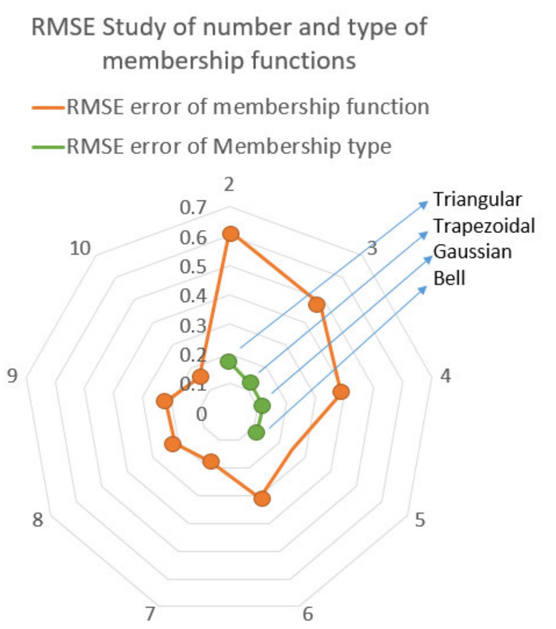

FIGURE 11. RMSE error of the number and type of membership functions.

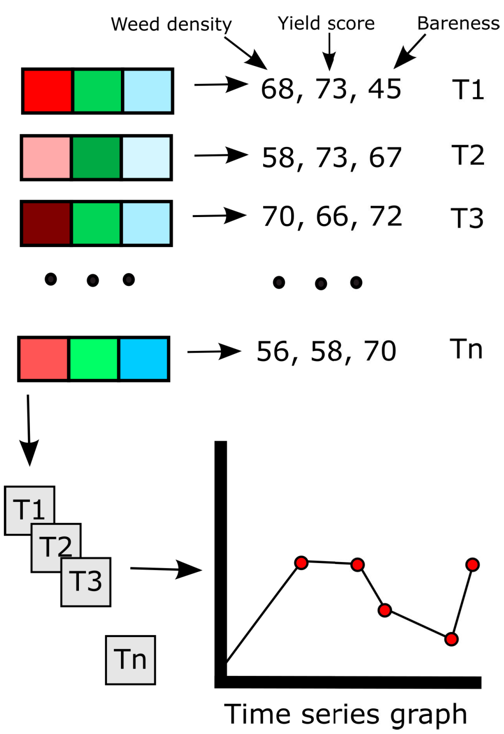

FIGURE 12. The time-series creation of fuzzy inference system.

Figure 15 shows that increasing the prediction ratio of UoI leads to a more conservative model, resulting in fewer detected masks. On the contrary, a lower prediction ratio will lead to more masks being detected, as the model becomes less strict in its criteria.

Figure 16 illustrates this trend, the two images display the model's output for different UoI prediction ratios.

Algorithm 1 The Algorithm of Calculating a Yield Score for a Pasture and the Fuzzy System Evaluation

Input: N: Number of images for a pasture
Image processing section
for *1 to N* **do**
  Calculate the weed density of image(i)
  Calculate the bareness of image(i)
end
Quantification section
For each image produce the crisp numbers of weed density and bareness
Fuzzy inference section
Fuzzify the weed density and bareness values
Incite the rules
Calculate the fuzzy score for each image
Defuzzify
Average the scores of all images of pasture
Result: Scoring section
ANFIS: The Neuro Fuzzy evaluation section
Prepare the yield score data as paired data for training set
Configure the fuzzy structure
for *1 to Epochs* **do**
  Train the weights(j) of neurons of ANFIS
  Apply the changes to weights
  Record the RMSE
end
Output: The last RMSE

By setting a low UoI prediction ratio of 0.74, the model detects around 500 masks. In contrast, setting a higher prediction ratio of 0.92 results in the detection of only 100 masks. This highlights the importance of studying and properly setting parameters such as UoI in determining the model's behaviour.

C. A PREDEFINED DASHBOARD FOR DAIRY FARMERS

This section presents a recommended Graphical User Interface (GUI) for dairy farmers, which can be used for data upload and model training as services for pasture management. Figure 17 shows a predefined dashboard that can be used during data entry and model training for pasture management. To avoid complexity, the GUI includes simple controlling components for image upload and model type. The user can also define the parameters of a fuzzy inference system, such as input type and the number of fuzzy rules. The trained models and resulting 2D maps can be downloaded and used.

D. A COLLABORATIVE FRAMEWORK FOR DAIRY FARMERS

The power of our fuzzy inference system is not limited to assessing pastures and recommending actions for weed monitoring, but also in generating pasture data as historical knowledge. Other potential contributions of our system could be:

FIGURE 13. The snapshot of image scales.

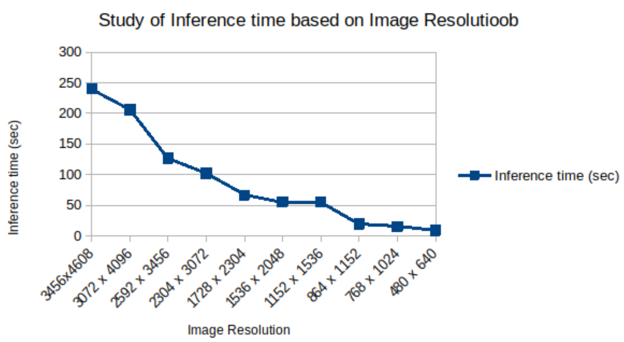

FIGURE 14. The inference time analysis of SAM.

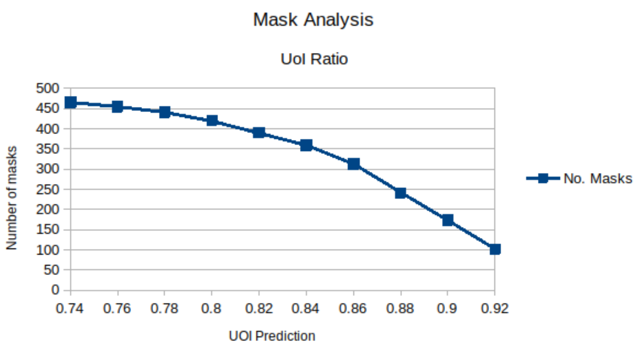

FIGURE 15. The mask analysis of SAM.

1) A pasture dataset that comes from pasture monitoring of weed density, bareness and yield score
2) A federated model that comes from aggregation of local models of dairy farmers

A pasture dataset can be created when the system is producing yield scores according to weed density and bareness. Each time of monitoring can result in a new row of a dataset

FIGURE 16. The mask output of two images by SAM.

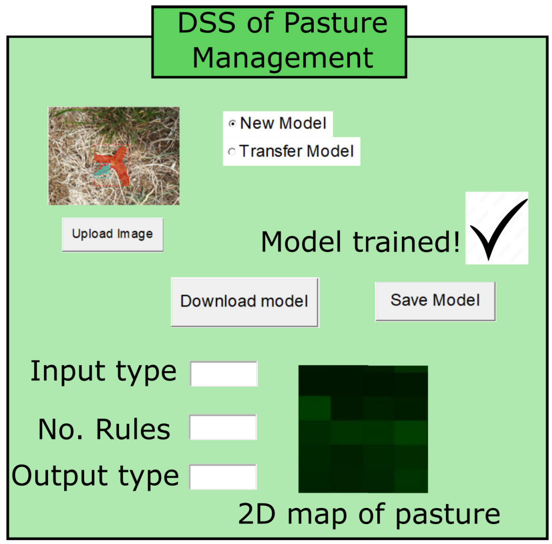

FIGURE 17. The Dashboard of DSS model for pasture management.

and by adding more data we can have a more sophisticated knowledge of a particular pasture. We can even include environmental variables such as temperature, wind, humidity, moisture, rain, pressure, etc in the dataset and calculate cross correlations among them to gain new knowledge. If any weed action is conducted, the monitoring tasks can provide the impact of the action, which can be used in the dataset for more accurate knowledge.

In federated learning, a number of local models (any type of object detection) are aggregated in a server for a more accurate model. In this method, each local model is labelled and saved. It is then transferred to an enterprise storage server to be processed and aggregated. The global model from the aggregated models can then be sent back to the local users, improving their weed detection and pasture assessment.

With these two concepts we can define an innovative architecture for a collaborative weed management system that helps farmers to use the service of monitoring weeds but in the meanwhile collaborating to the knowledge of weed

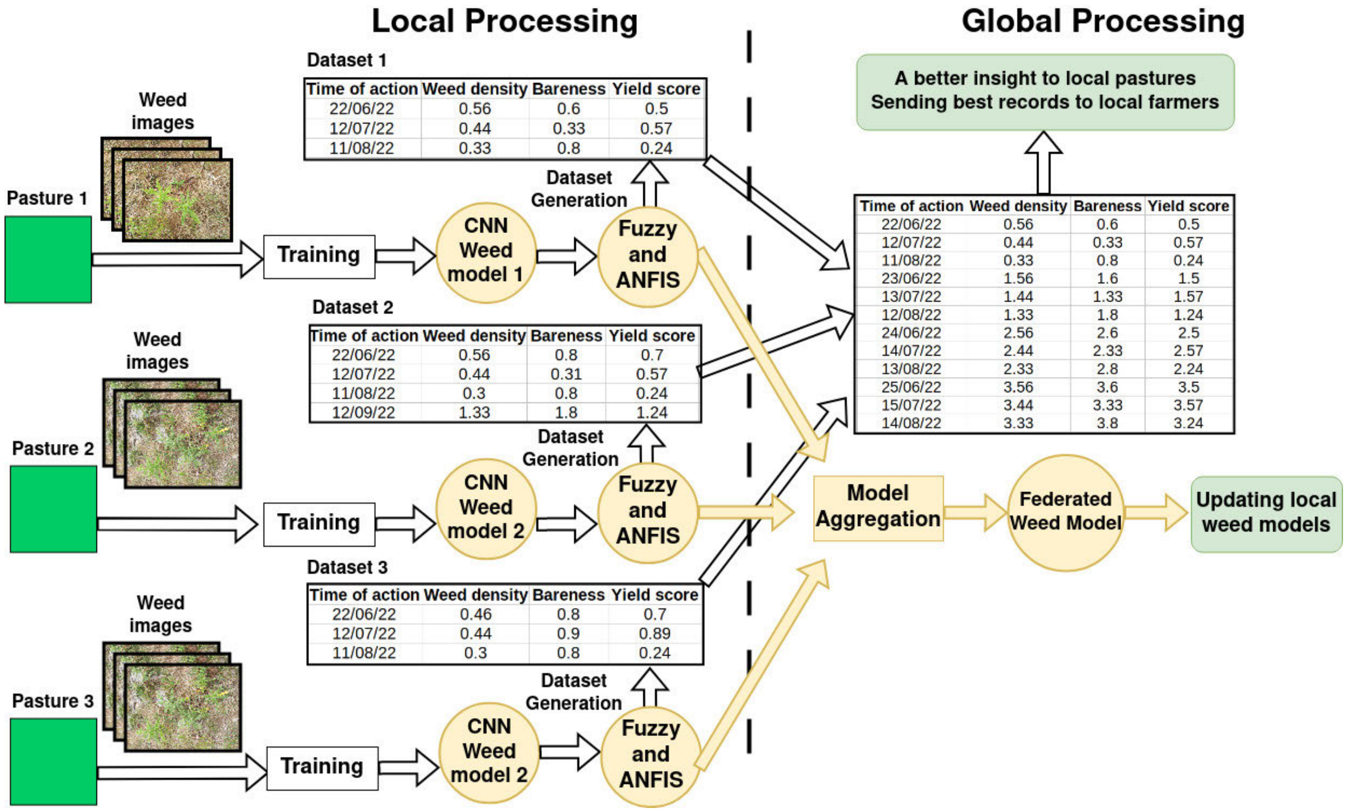

FIGURE 18. A weed management architecture based on weed dataset and federated mdoels.

management at the same time. Figure 18 shows the proposed system architecture.

V. LIMITATION

For this study, we faced limitations in accessing a pasture to take photos and collect images. We initially planned to conduct our experimentation on a real pasture using tiling images, but due to COVID-19 restrictions, we experimented with a simulation map. Additionally, Python does not have a package or library for coding Adaptive Network-based Fuzzy Inference System (ANFIS) and training the fuzzy model, so we performed our training experimentation using the ANFIS model in MATLAB.

VI. CONCLUSION AND FUTURE WORK

This research integrates several Artificial Intelligence (AI) models and topics: an object detection model, a fuzzy inference system, Adaptive Network-based Fuzzy Inference System (ANFIS), and a time-series analysis. Our work has contributed to scoring and recommending actions for dairy farmers, which has not been previously conducted. As dairy farmers in New Zealand lack technological tools for managing their pastures, the proposed system can help them understand their pastures and manage them systematically. Processing two random variables of weed density and the bareness of a pasture can provide sufficient knowledge for dairy farmers, helping them to have much better pasture monitoring.

As future work, one can study the influences of other variables such as temperature, humidity, and wind on pasture productivity. A longitudinal study on the improved productivity of using the Decision Support System (DSS) would provide insight into how weed invasion starts, spreads, and is controlled, and how effectively seeding covers bare patches. Satellite images can be another useful source for weed controlling and covering bare patches of pastures. Adopting more advanced object detection algorithms for measuring weed density will also improve pasture productivity.

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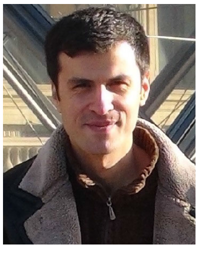

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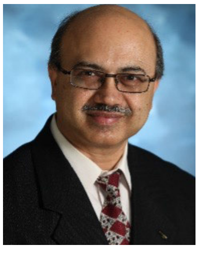

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