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A REVIEW OF MULTIBAND IMAGING TECHNIQUES IN AGRICULTURE

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Abstract: The multispectral imaging method entails collecting and processing an image through different wavelength bands on the electromagnetic spectrum. The imaging method is entirely different from the conventional imaging technique since it does not objective one specialized wavelength band or channel such as visible light. In its place, it collects and processes various spectral bands of information either simultaneously or one by one. This provides a deeper insight into the subject matter being analyzed. The multi-band or multi-spectral imaging process involves gathering various bands of wavelengths to form a full spectrum of the view of an object or image. In this case, each wavelength corresponds to a specified region on the electromagnetic band, including visible light, infrared light, and ultraviolet light. This means that multiband imaging provides a more comprehensive analysis of the situation than single-channel images that have a limited scope of wavelengths. It is vital in numerous areas, particularly those involving the use of machine vision cameras such as agriculture, medicine, and others. Due to population increases, natural resource exhaustion can be expected; therefore, farming production must be improved.

Keywords: Multiband Imaging, Agriculture Technology, Precision Agriculture, Multispectral Sensors

Introduction: Multiband imaging is a technique that captures and analyzes images across multiple wavelength bands of the electromagnetic spectrum. Unlike conventional imaging methods that focus on a single spectral band, such as visible light, multiband imaging collects information from several distinct spectral bands simultaneously or sequentially. This capability enables a more detailed and comprehensive analysis of objects and scenes under investigation. By combining information from different wavelength regions, including visible, infrared, and ultraviolet spectra, multiband imaging provides richer information than traditional single-band imaging systems. [2,3]

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Multispectral and hyperspectral imaging techniques have found widespread applications in agriculture, healthcare, remote sensing, environmental monitoring, and machine vision systems. As global population growth increases the demand for food production while natural resources become more limited, advanced imaging technologies have become increasingly important for improving agricultural productivity and maintaining quality standards. Multiband imaging enhances inspection and monitoring processes by providing detailed spectral information that is not available in conventional RGB images.

Multiband images are extensively used in remote sensing and satellite imagery because they provide more comprehensive information about the physical and chemical properties of objects and surfaces. In a study by the authors of Reference [4], a Joint Encryption and Compression Algorithm (JECA) was proposed for multiband remote sensing images. Experimental results demonstrated that the proposed method reduced training time by approximately 50% compared with existing joint encryption and compression techniques while maintaining comparable compression performance. Furthermore, the proposed approach achieved enhanced security performance, making it suitable for multiband remote sensing applications. [4]

In the medical imaging domain, researchers proposed an innovative image-encryption technique based on a five-dimensional (5D) multi-spectral multi-wing chaotic system and QR decomposition.[5] The proposed method introduced a five-dimensional chaotic system with a feedback controller to generate a larger Lyapunov exponent, thereby enhancing system complexity and security. QR decomposition was employed to separate both the plaintext image matrix and chaotic sequence into orthogonal and upper-triangular matrices. Subsequently, the orthogonal matrices were combined using a chaotic sequence control mechanism, while an improved Joseph-loop algorithm was applied to process the triangular matrices before multiplication. Finally, bit-level shuffling was performed to generate the encrypted image. Experimental results demonstrated a large key space, high key sensitivity, and strong resistance against statistical and gray-value analysis attacks. [5]

Deep-learning approaches have also been integrated with multiband imaging for advanced image analysis tasks. In Reference [7], a two-stage encoder–decoder framework was proposed for brain tumor sub-region segmentation. Variational autoencoder regularization was incorporated into both stages to reduce overfitting. The second stage employed attention mechanisms and was trained using features generated from the first stage, resulting in improved segmentation performance and enhanced feature representation. [7]

Image segmentation remains one of the most important applications of multiband imagery. In Reference [1], a scalar-based multiband image segmentation approach was proposed. The method consisted of three primary stages: band selection to eliminate irrelevant information, histogram-based multi-threshold segmentation of each selected band, and fusion of segmented bands to generate the final segmentation result. The effectiveness of the approach was validated using high-resolution multispectral imagery obtained from the Compact Airborne Spectrographic Imager (CASI), demonstrating its applicability to real-world remote-sensing scenarios. [1]

Recent research has also focused on reducing the number of spectral bands required for efficient deep-learning implementations. According to Reference [6], a lightweight convolutional network known as LC-Net was developed to minimize the number of input bands while maintaining segmentation performance. Experimental results on the RIT-18 dataset showed that integrating LC-Net into the network architecture increased Overall Accuracy (OA) by 12.1% and Mean Accuracy (MA) by 14.03%. Furthermore, LC-Net slightly outperformed the optimal three-band combination identified through exhaustive search while significantly reducing computational complexity and operational costs. These findings highlight the practical advantages of lightweight multiband processing techniques for real-world applications. [6]

Overall, the literature demonstrates that multiband imaging provides substantial advantages over conventional imaging techniques by offering richer spectral information and improved analytical capabilities. Applications ranging from remote sensing and medical imaging to image segmentation and deep-learning-based classification have shown significant performance improvements through the use of multiband data. Consequently, multiband imaging has become an increasingly important technology in modern agricultural systems, where accurate monitoring, disease detection, and resource management are essential for sustainable agricultural development.

Multibans imaging and its applied areas: Multiband image segmentation is a process used in image evaluation that involves splitting an image with multiple spectral bands into distinct regions or segments based on specific criteria. This procedure is often applied in remote sensing and various scientific fields where images capture data across different wavelengths or spectral bands[1].

The research examined the pertinency of TerraSAR-X and Radarsat-2 remote sensing datasets in the assessment of soil vapor of bare agricultural soils, employing empirical and semi-empirical methods. Empirical method entailed utilizing SVR in which one or two bands (i.e., C-band and X-band) were operated for prediction. The semi-empirical method entailed using Dubois model based on SAR data to guess the surface soil moisture content. Carried out at two bare agricultural field sites with in-situ measurements, the results indicated that TerraSAR-X and Radarsat-2 data sets are useful in guessing surface soil moisture with accuracy of about 3% RMSE. TerraSAR-X data yielded better accuracy compared to Radarsat-2 data. Combining both C-band and X-band improved accuracy further by yielding RMSE value of about 2.2%. The performance of modified Dubois model was similar to the empirical model regardless of surface roughness. It can be determined that multiple band SAR datasets can be effectively used in soil moisture estimation in bare fields. Future investigate should emphasis on vegetation covers. Multi-band SAR satellites are making progress in land surface parameters inversion[9] in figure 1.

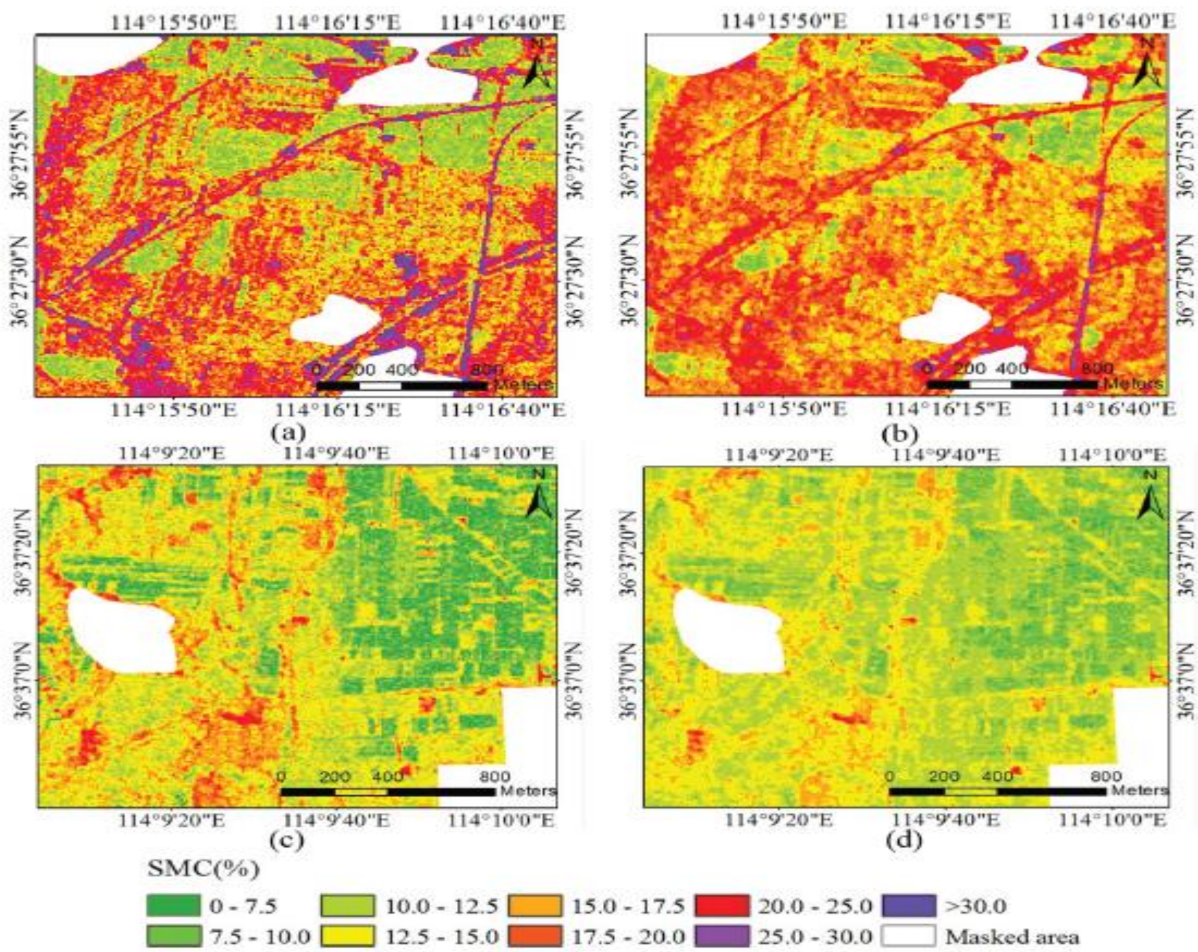

Figure 1. Maps of soil moisture levels (a) Jiulong region using SVR algorithm; (b) Jiulong region using modified Dubois method; (c) Wannian region using SVR algorithm; and (d) Wannian region using modified Dubois method. White areas represent rural zones[9].

SAM is an adaptable image segmentation model capable of segmenting numerous objects in any images with the help of different prompts. SAM is not suitable for performing agricultural functions such as crop disease and pest segmentation. To overcome the restrictions of the model, an agricultural SAM adapter (ASA) is used. In this instance, agricultural knowledge is injected into SAM using the simple adapter mechanism. It makes use of certain characteristics of agricultural images with prompts to perform zero-shot segmentation. It has been supported through several experiments that the proposed agricultural adaptation helps in enhancing the segmentation performance of 12 agricultural datasets by 41.48% regarding the segmentation of coffee leaves affected with diseases. The ASA adapter successfully modifies the generalized SAM model to produce outstanding results concerning pest and leaf diseases segmentation[10]. Comparison between ASA and SAM models in relation to image segmentation performance for agricultural pests is illustrated in the following table 1.

Table 1. Evaluation of ASA and SAM effectiveness in image segmentation

Segmentation Target	mDice (%)			mIoU (%)		
	SAM	ASA	Improve	SAM	ASA	Improve
Cydia pomonella	88.11	95.32	7.21	82.52	91.22	8.70
Gryllotalpa	74.38	93.06	18.68	66.34	87.51	21.17
Leafhopper	91.71	95.84	4.13	86.74	92.20	5.46
Locust	71.42	91.47	20.05	63.58	85.16	21.58
Oriental fruit fly	77.36	92.02	14.66	69.58	85.96	16.38
Pieris rapae Linnaeus	93.61	97.19	3.58	90.90	94.76	3.86
Snail	92.44	95.50	3.06	88.96	92.10	3.14
Spodoptera litura	89.33	92.95	3.62	84.64	88.17	3.53
Stinkbug	78.53	93.97	15.44	71.20	89.08	17.88
Weevil	85.49	94.20	8.71	79.21	89.45	10.24
Average	**84.24**	**94.15**	**9.91**	**78.37**	**89.56**	**11.19**

Semantic segmentation affects the understanding of images throughout a wide range of domains. Now it has become a crucial research topic. The developments in deep learning have been significant. This has enhanced the processing of farm images through combining the new methods with traditional approaches. The semantic segmentation transformed the farm automation. It is important to analyze crops for detecting pest infestations and diseases. The current review examines the latest developments in farm image segmentation. It describes both existing methods and recently proposed techniques. The effectiveness and applications of the methods are discussed in figure 2. Several issues also are pointed out. More labeled training data should be collected. The current approaches are not robust and universal enough. It is necessary to expand available datasets or incorporate additional information sources into existing methods. This review proves the rapid development of segmentation technology in agriculture. It can be manipulated for identifying stressed plants and assessing erosion and the environmental state. The advancements associated with CNNs and other related approaches are described in. Older techniques usually are used for pre-processing or as a component of deep learning algorithms[12].

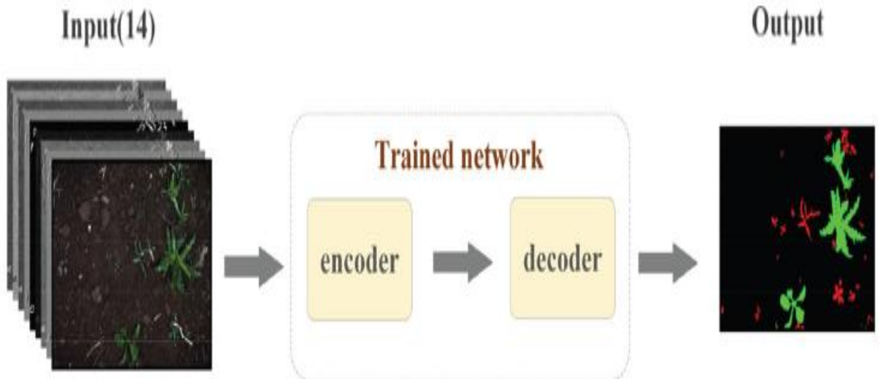

Figure 2. The segmentation outcome of an Encoder-Decoder network utilizing multiple image channels as input data[13].

With the raising global population, climate change, and rising demand for high-quality, eco-friendly food, plant breeders are working on creating crops with higher yields by monitoring plant phenotypes. Traditional methods for tracking new crop varieties are slow and subjective, often relying on microplot subsampling. High-throughput phenotyping using drone-acquired aerial images speeds up and simplifies this process. Accurate identification and localization of microplots from these images are essential. This manuscript examines recent developments in vegetation and microplot segmentation, focusing on general methods using indices and learning techniques, alongside machine learning and image processing for microplots. Analyzing 92 studies, the review highlights the promise of machine learning and deep learning models, such as DeeplabV3+, U-Net, and SegNet, compared to traditional color-based methods. High-throughput phenotyping aids in plant breeding and crop management, though manual and semi-automatic methods still require significant labor. Overall, advanced machine vision techniques offer a valuable tool for precise vegetation and microplot segmentation in plant phenotyping[14].

This article explains a system that applies the use of unmanned aerial vehicles (UAVs) for conducting comprehensive analyses of the crops by applying both qualitative and quantitative methods of assessment for effective agriculture management in table 2. The system uses Detectron2, which is a deep learning demonstrate based on a convolutional neural network for object detection and segmentation within images. The model trained using a dataset with COCO format, having different types of objects labeled, provides the basis for analyzing multispectral images. It has a frontend for user interfaces and annotations, as well as a backend for handling image analysis, project management, and polygon operations. The users will be able to specify an area for their analysis and carry out the analysis with the use of either NDVI or OSAVI. To conduct quantitative analysis, the system relies on a pre-trained deep learning model to count and identify specific objects, particularly young lettuce crops. Its accuracy measured with Average Precision (AP) has proven excellent results; nonetheless, some obstacles have been noticed with the model to generalize the features of undetected lettuces. Possible upgrades include increasing data sets and solving problems related to overfitting.

Table 2. Segmentation Masks Through Different Ap Metrics.

Prediction	**AP**	**AP50**	**AP75**
Bounding boxes	56.096	89.069	66.683
Segmentation masks	54.253	89.069	58.230

The use of multispectral imagery has become prevalent in agriculture when performing such operations as image segmentation, crop monitoring, field robotic operations, and yield estimation. In this research paper, thought is paid to improve image subdivision with fusion techniques. Specifically, it is discussed how combining RGB images and NDVI allows detecting crop rows and is useful for field operations performed by autonomous robots. The study assesses several fusion methods considering classical image segmentation and deep studying image division about early and late fusion. By using two agricultural image databases, researchers come to conclusion that classical image segmentation procedures like edge detection and thresholding work well and sometimes even compete with deep learning, especially for foreground-background segmentation. Considering the fusion methods, researchers conclude that the most effective technique is late fusion that shows higher adaptability. Thus, classical image segmentation techniques should not be neglected as they have practical applications. The table 3 demonstrates segmentation quality of Maize[15].

Table 3. Segmentation performance of the maze and vine

	Dataset / Method	Maize			Vine									Average		
		VG			Qta. Baixo			ESAC			Valdoeiro					
		Acc.	F1	IoU	Acc.	F1	IoU	Acc.	F1	IoU	Acc.	F1	IoU	Acc.	F1	IoU
OTS	RGB	74.4	28.3	16.7	57.6	41.9	27.6	79.1	52.7	40.2	74.5	38.6	26.0	71.4	40.4	27.6
	NDVI	76.1	32.3	19.6	84.1	61.7	46.1	65.6	49.7	34.8	92.4	67.8	56.0	79.6	52.9	39.1
	Early F.	75.6	34.1	20.9	71.6	52.7	37.7	71.4	55.5	41.2	89.5	65.3	52.7	77.1	51.9	38.1
	Late F.	67.5	33.7	20.8	83.0	67.5	44.7	89.5	66.8	42.9	91.6	81.6	56.7	**82.7**	**62.4**	**41.3**
Edge-b.	RGB	76.6	12.9	6.9	69.8	15.5	8.5	78.1	26.3	15.4	86.9	22.7	13.1	77.9	19.4	10.5
	NDVI	75.6	13.0	7.0	70.3	16.8	9.3	61.1	18.7	10.4	94.2	48.6	33.7	75.3	24.3	**15.1**
	Early F.	84.1	21.0	11.9	76.8	16.3	8.9	65.4	14.8	8.0	93.9	39.3	25.8	**80.1**	22.9	13.7
	Late F.	70.1	14.0	7.6	64.8	18.9	10.6	71.1	25.5	14.8	87.6	39.1	25.1	73.5	**24.4**	14.5
Region-b.	RGB	84.1	21.0	11.9	78.3	47.4	33.1	78.9	44.3	33.2	85.3	44.6	31.2	81.7	39.3	27.4
	NDVI	82.2	12.4	6.7	89.0	67.9	52.5	76.0	50.9	37.3	97.2	76.3	63.8	86.1	51.9	40.1
	Early F.	76.7	19.0	10.5	81.3	52.7	37.0	87.6	63.5	49.8	97.3	77.6	65.2	85.8	53.2	**40.6**
	Late F.	81.8	25.3	14.7	93.1	69.3	34.9	92.1	48.9	24.6	98.6	82.7	45.2	**91.4**	**56.6**	29.9
SegNet	RGB	96.2	87.1	78.5	84.9	52.1	35.6	73.1	41.9	27.7	92.1	58.0	41.3	86.6	59.8	45.8
	NDVI	95.6	85.3	76.1	85.9	64.4	48.4	78.5	51.4	36.8	93.9	67.1	51.7	**88.5**	**67.1**	**53.3**
	Early F.	96.8	89.3	80.8	81.1	42.1	26.7	81.4	50.5	33.9	94.3	61.0	43.9	88.4	60.7	46.3
	Late F.	96.1	86.9	78.6	86.2	56.4	40.4	75.9	46.9	33.0	93.4	61.4	45.7	87.9	62.9	49.4
DeeplabV3	RGB	96.5	87.9	79.8	81.8	35.6	21.8	82.0	45.0	30.1	91.0	56.2	39.7	87.9	56.1	42.9
	NDVI	95.9	86.0	77.3	87.3	59.2	42.2	77.7	33.8	21.4	89.1	44.2	28.8	87.5	55.8	42.4
	Early F.	97.3	89.2	81.2	82.1	31.0	18.7	79.9	37.3	23.8	89.9	52.8	36.4	87.3	52.6	40.0
	Late F.	96.6	87.7	80.2	85.3	47.5	32.0	81.0	39.0	25.9	92.5	58.0	42.3	**88.9**	**58.1**	**45.1**

For instance, the study carried out in is established on the assessment of remote sensing satellite image information using machine learning models; however, in the current case, the data source considered is specifically the Sentinel-2A satellite copy data. The feature selection methods to address classification problems include index-based classification (NDVI, NDWI), index connected bands-based classification (Bands 4, 8A, and 11), MI score-based bands classification (Bands 6, 7, 8, 8A, 9, 5, and 3), and all bands classification. In particular, the case analysis of land cover classification including five types shows that the most successful approach is based on all available Sentinel-2A bands classification.

In general, grouping methods that utilize exact appropriate groups with supervised learning techniques surpass traditional index-based approaches. The absolute use of Sentinel-2A's spectral bands addresses some limitations of index-based methods. This method is also suitable for monitoring forest vegetation, assessing vegetation biological conditions, and making irrigation decisions.

There are many multi-band or multispectral datasets used in various application areas. The researcher[6] compared the common multispectral dataset as shown in table [4].

Table 4. Overview Of Five Frequently Utilized Multiband Datasets

Dataset	Sensor(s)	GSD (m)	No. of Classes	No. of Bands	Distribution of Bands
Vaihingen	Green / Red / IR	0.09	5	3	Green, Red, IR
Potsdam	VNIR	0.05	5	4	Blue, Green, Red, NIR
Zurich Summer	QuickBird	0.61	8	4	Blue, Green, Red, NIR
L8 SPARCS	Landsat 8	30	5	10	Coastal, Green, Red, NIR, SWIR-1, SWIR-2, Pan, Cirrus, TIRS
RIT-18	VNIR	0.047	18	6	Blue, Green, Red, NIR-1, NIR-2, NIR-3

The researcher of[7] utilized the BraTS 2020 training dataset to perform brain tumor segmentation, which is essential for diagnosing diseases, supervising conditions, and planning treatments. The researcher[9] obtained Radarsat-2 and TerraSAR-X data for estimate soil moisture content, alongside detailed statistics on the SAR data as shown in table 5.

Table 5. Comprehensive details on the SAR data

SAR Data	Acquisition Date	Band	Frequency	Incidence Angle	Imaging Mode	Resolution
Radarsat-2	28 April 2015	C	5.3 GHz	36°	Multi-Look Fine	5 m
TerraSAR-X	29 April 2015	X	9.6 GHz	26°	Strip Map	3 m

Methodology using multiband imaging: NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) are tools that can be employed in remote sensing analysis and classification. NDVI helps evaluate the density of vegetation cover through the ratio of red and near-infrared bands, thereby making it possible to distinguish vegetation from bare surfaces. On the other hand, NDWI helps identify surface water through the ratio of green and near-infrared bands, thereby making it possible to distinguish water from any kind of land type[16].

Categorization based on indices-related bands involves utilizing spectral groups involving Red, NIR and SWIR from an image to compute indices, which assist in categorizing and examining various types of land cover.

MI band-based classification utilizes spectral bands selected through Mutual Information to improve the accuracy and efficiency of classifying and analyzing images[8]. Table 6 specifies a summary of how categorization performance has been augmented with the application of different algorithms.

Table 6. Categorizing five land cover types[8].

Classification Algorithms	**Crop**	**Tree**	**Soil**	**Water**	**Road**	**overall accuracy**
Indices based classification	97.5%	80.0%	71.8%	87.2%	75.6%	87.7%
Indices related to band-based classification	98.5%	91.1%	88.5%	90.0%	79.9%	93.2%
MI bands-based classification	98.8%	92.9%	96.2%	91.9%	91.4%	95.8%
Full bands-based classification	99.8%	95.5%	98.2%	96.9%	93.8%	97.9%

Experimental result: This section reviews the methods proposed by various authors and their different optimal results in specific application areas. Table 7 specifies a brief of the experimental results from various proposed methods.

Table 7. Evaluation of various proposed methods

Application Area	**Methodology**	**Result**
Enhancing Agricultural pest Image Segmentation [10]	Agricultural SAM adapter (ASA), integrates agricultural expertise into segmentation models using an effective adapter technique.	94.15%
Quality and quantity segmentation of lettuce [11]	Detectron2 and Normalized Difference Vegetation Index (NDVI)	89%
Segmentation effectiveness for Vineyard dataset [15].	The classical segmentation of region-based with late fusion.	91.4%
Segmentation effectiveness for Maize dataset [15].	Deep Learning segmentation of DeeplabV3 with late fusion	88.9%
Assessing and Estimating Soil Moisture Levels [9].	Support Vector Regression (SVR) with TerraSAR-X and Radarsat-2	97.79%

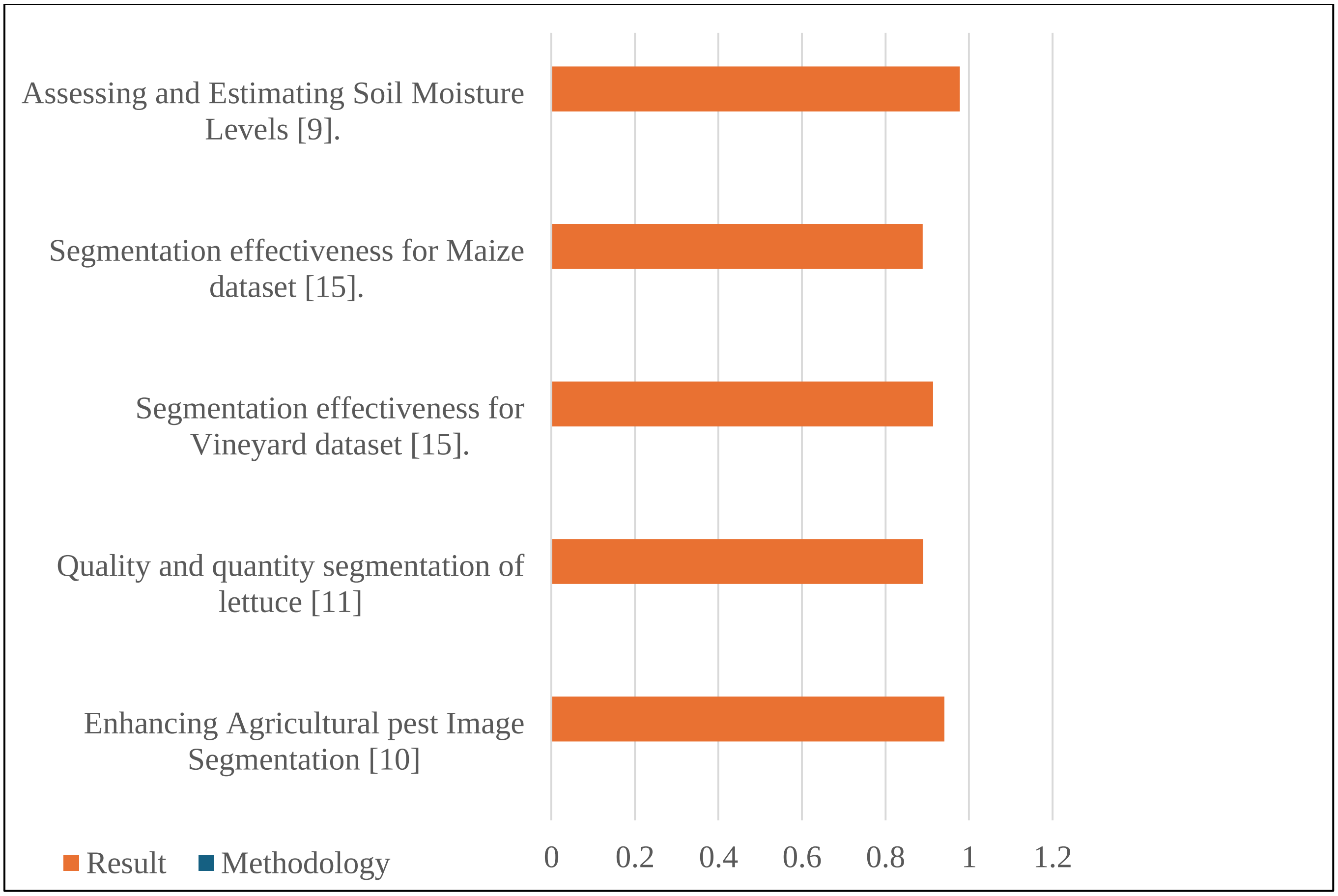

Figure 3. Comparison of Results

Conclusion: The advances made in imaging technology have played an important role in revolutionizing agriculture in terms of crop growth and development, soil condition monitoring, and general farm management. The review seeks to explore the revolutionary changes brought about using multiband imaging technology that uses different bands of the spectrum to enhance crop management and monitoring. Not only does the review bring together recent developments and ongoing research in multiband imaging technology, but it also covers the system for future developments in the field.

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