Journal of Climate and Community Development

A Double-Blind, Peer-Reviewed, HEC recognized Y-category Research Journal

E-ISSN: 3006-7855 P-ISSN: 3006-7847

Computer Vision and Deep Learning for Climate-Resilient Agriculture: Improving Soil Health, Crop Protection, and Community Livelihoods

Basit Amin[1] Jawaria Nasir[2] Dr. Imran Khan[3] Hussain Shah[4]

[1] Department of Computer Science, Comsats University, Islamabad, Pakistan.

[2] Lecturer, Department of Statistics Federal Urdu University, Arts Science and Technology, Karachi, Pakistan.

[3] Assistan Professor, Department of Artificial Intelligence, Dawood University of Engineering and Technology, Pakistan.

[4] Lecturer, Shaikh Zayed Islamic Centre, University of Peshawar, Pakistan.

Corresponding Author: Basit Amin, **Correspondence through:** basitaminsidhu@gmail.com

Vol. *5,* ***Issue*** *2, 2026*

Article Information

Received:

2026-06-05

Revised:

2026-07-30

Accepted:

2026-08-16

ABSTRACT

Agricultural productivity and rural livelihoods are under threat from climate change, soil degradation, crop diseases and outbreaks of pests, and intelligent and resilient farming systems are needed. The study focused on the potential use of computer vision and deep learning to enhance soil health monitoring, protection of crops, adaptation to climate change and community livelihoods. The design was quantitative with the use of a structured questionnaire with 5-point likert scale for data collection, from a sample of 300 farmers and agricultural stakeholders. Descriptive statistics, reliability analysis, Pearson correlation, and multiple regression were applied to analyze the data. The findings showed high mean scores for computer vision ($M = 4.18$, $SD = 0.62$), deep learning ($M = 4.24$, $SD = 0.59$), soil health ($M = 4.07$, $SD = 0.67$), crop protection ($M = 4.31$, $SD = 0.55$), climate resilience ($M = 4.16$, $SD = 0.61$), and community livelihoods ($M = 4.09$, $SD = 0.64$). The analyses showed that computer vision ($\beta = 0.39$, $p < 0.001$) and deep learning ($\beta = 0.48$, $p < 0.001$) significantly predicted the variance of climate resilience (62%). The predictors accounted for 67% of variance in crop protection, and the deep learning had the larger contribution ($\beta = 0.52$, $p < 0.001$). The research demonstrated that incorporating computer vision and deep learning can boost agricultural monitoring, protection, climate adaptation, and livelihood resilience. The results suggest investment in affordable, farmers tailored, locally adaptable AI solutions for sustainable agriculture.

Keywords: *Agriculture, Climate Resilience, Computer Vision, Deep Learning, Crop Protection, Soil Health.*

Citation: APA

Amin, B., Nasir, J., Khan, I & Shah, H (2026). Computer Vision and Deep Learning for Climate-Resilient Agriculture: Improving Soil Health, Crop Protection, and Community Livelihoods, Journal of Climate and Community Development, 5(2), 149-162.

Introduction

Climate change is increasingly impacting agricultural systems increasing the frequency of certain diseases (pest and pathogen diseases), impacts of one and two-day droughts and floods, soil erosion, and increasing mean temperatures. they directly affect food production and profitability at livestock farming enterprises, as well as the livelihoods of the farming household-consumers in rural areas, particularly in developing nations where producers might not have the same opportunities to make use of the latest agricultural technologies. The goal of climate resilient agriculture is to improve the productivity and at the same time strengthen the resilient capacity of the agriculture system to face environment stresses/changes. This can be made possible using digital technologies, that are able to send information related to crop conditions and conditions of the environment in real time and increase the farmers' capacity to make their decisions on their farms.

In the traditional approach, efficiency of agricultural monitoring is achieved through physical field inspections and laboratory evaluations which are time, labor and cost consuming. The alternative is by computer vision and the agricultural images captured with smartphones, drones and other technology tools can be automatically analyzed. CNNs are efficient deep learning models, which can detect complex visual patterns linked to crop diseases and pest damage, weeds, and plant stress. Numerous deep learning studies prove that it has significant possibility of classification and monitoring in agricultural images and can help to detect the problems at an early stage, which can help achieve more targeted interventions (Kamilaris & Prenafeta-Boldú, 2018; Koirala et al., 2019).

The ability to correlate crop protection to resource efficient management of agricultural systems, using computer vision and deep learning, is another potentially broader climate-resilience area. Early detection of disease and pest infestations can minimize crop damage and avoid unnecessary pesticide use, and then the image could be monitored to help better inform agricultural decision making. On the other hand, new-AI technologies could help farmers to adjust to environment changes by improving the monitoring of meteorology information and predicting it. However, these technologies function when data is good, cost affordable, digital infrastructure is already in place, and when farmers are trainable and are ready to accept the technologies. Therefore, technological performance and the sustainability and inclusive effect it has on agriculture are also needs to be addressed alongside the sustainability and inclusive effects it has on agricultural development (Liakos et al., 2018; Javaid et al., 2023).

Background of the Study

Soil health is a core component of soil quality that influences soil water and nutrient supply, plant growth and development, and ecosystem stability – is crucial for productive and climate resilient agriculture. Over intensity, soil degradation due to climate change, salinity and a slow decline in soil organic matter reduce the productivity of the land further and place a greater stress on farmers from the environment. Soils assessment is generally conducted in laboratories and on the field with soil samples, which is usually a challenging process for smallholders as they need technical facilities, distance and cost to get soil samples. Combined with other digital technologies, the use of remote sensing has the potential for providing additional spatially specific data on soil and vegetation conditions in addition to traditional assessments (Mulla, 2013).

By analyzing vast amounts of visual data and discovering patterns and connections that would be challenging for humans to notice, computer vision and deep learning can bolster agricultural monitoring efforts and gain valuable insights. An image-based system can help detect diseases, nutrient deficiencies, pest attacks, weeds and visible signs of stress in the plants located inside the crop. All these technologies as well as remote sensing and in-field information can help with precision agriculture and in making decisions around irrigation, fertilization, crop protection and resource allocation decisions at field scale. Driven by the need for faster and more efficient agricultural decision making, and by the need for more targeted farming, machine learning research has demonstrated its potential in agriculture, as systems based on AI algorithms can benefit at these two aspects (Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2018).

The impact of these technologies is not just that of production and productivity, but also that of the economic and social viability of the farming community. Crop loss and soil productivity loss will result in lower household income, higher production costs and food security. Crop monitoring can offer farmers information in real time, with the help of AI, that allows for early intervention and can minimize the avoidable losses in agriculture. But the difference in digital infrastructure access and digital literacy, the high cost of digital technology and lack of technical support might be a restriction on the level of digital adoption by smallholder farmers. Thus, making these Computer Vision and Deep Learning tools accessible, usable, and taking into account the agro ecological system, is crucial to make a valuable contribution to sustainable livelihood and communities' resilience (FAO, 2022; Javaid et al, 2023).

Objectives of the Study

1. To examine the application of computer vision and deep learning for monitoring soil health and identifying soil-related conditions affecting agricultural productivity.
2. To assess the effectiveness of computer vision and deep learning in detecting crop diseases, pests, and other forms of crop stress for improved crop protection.
3. To evaluate the contribution of AI-based agricultural technologies to climate resilience, sustainable farming practices, and community livelihoods.

Research Questions

Q1. How can computer vision and deep learning be applied to monitor soil health and soil-related agricultural conditions?

Q2. How effective are computer vision and deep learning technologies in detecting crop diseases, pests, and crop stress?

Q3. How can AI-based agricultural technologies contribute to climate resilience, sustainable farming, and improved community livelihoods?

Significance of the Study

This paper is relevant as it looks at using computer vision and deep learning to contribute to climate-resilient agriculture, and introduces the blending of technology and sustainable farming practices. The results assist farmers or agricultural practitioners to detect early signs of crop diseases, pests and visible issues related to soil problems and can act as the basis for interventions, as soon as possible and targeted. Research can also contribute to policy and agricultural organizations understanding the potential of AI powered tools to enhance resource efficiency, mitigate crop losses and grow resilience to climate changing pressures. Encouraging better monitoring and protection of crops for rural communities can aid productivity, sustainable income, food security, and livelihood resilience. The research builds upon the literature on AI, precision agriculture, soil health, and adaptation to climate change, emphasizing the potential for computer vision and deep learning to drive sustainable agricultural transformation.

Literature Review

Computer Vision and Deep Learning in Agriculture

A growing component of digital agriculture is computer vision that enables robots to “see” and make sense of the visual information found in crops, soil, handheld drones, and satellites. Although little manual feature engineering is necessary for these applications, the complex features are learned directly from agricultural images with deep learning (DL). Consistently, Kamilaris and Prenafeta-Boldú (2018) recognized as applications of deep learning, large potential possibilities of image-based agriculture classification, disease detection, weed detection and agriculture monitoring. Liakos et al. (2018) were motivated by machine learning for aspects like automatic processing of large and complex datasets for better agriculture decision making.

The images in agricultural applications have complex visual features related to plant color, texture, shape and disease symptoms, making convolutional neural networks (CNNs) a particularly relevant topic for discussion. In the same way, under controlled conditions, Mohanty et al. (2016) demonstrated the aptitude of using deep convolutional neural networks for crop disease recognition in terms of classification accuracy at leaf level achieving high classification accuracy. In addition, Koirala et al. (2019) mentioned deep learning, a system that can be beneficial for automated management of the crop throughout its development and for estimating the yield, through computer vision techniques. The results shed light on the potential of computer vision in reducing the manual inspection time requirement and as a means of providing scaled solutions in monitoring the agricultural conditions.

Photos taken under controlled conditions can contrast with photos taken out in the field due to different lighting conditions, background, weather, plant stage and/or disease. Though deep learning models excelled to diagnose plant disease neatly as was shown by Ferentinos (2018), using these models is still reliant on representative and of high quality training sets. Therefore, further efforts should include datasets coming down from the field, generalization of the model, explanation, computational efficiency and Deployment at affordable price. Such characteristics will be essential for AI systems to excel in the context of climate-resilient agriculture, as they are subjected to diverse conditions.

Sensors to Measure Soil Health & Crop Protection

Soil health plays a pivotal role in the sustainable production of agriculture as soil properties impact nutrient availability, water retention and holding capacity, plant growth and development, and ecosystem functions. Conventional soil sampling and soil chemistry laboratory testing are central to traditional soil assessment, which can hinder frequent monitoring if the land is extensive, such as on farms. Some of these challenges can be overcome by developing a remote sensing solution to produce spatial information on soil and vegetation conditions. Mulla (2013) explained that remote sensing has now been playing a more prominent role in precision agriculture and being seen as an enabler to assessment and management of agricultural resources at the spatial level. The combination of remote sensing and machine learning has the potential to improve further the processing and interpretation of complex information in the field of agriculture and environment.

The computer vision technology and machine learning also has the potential to be applied to crop protection and disease, weed, insect and ‘physiological stress' identification in relatively early stages. Mohanty et al. (2016) have thus provided a deep neural network algorithm to classify different plant disease datasets taken from plant leaves using the visual attributes of the plant leaf. Ferentinos et al. (2018) used deep learning models to also be able to detect plant diseases from leaf images for a range of different disease classes and crop classes. This kind of a system can help farmers get an early diagnosis and assist in offsetting the need for people to simply look at the number of sunspots. Targeted protection would be facilitated by early diagnosis (thus minimizing unnecessary pesticide use) and early containment of disease would be aided thereby.

There is a perspective in the literature that computer vision is not often used in isolation, but may be used in combination with other sets of data to gain greater agricultural intelligence. Can also be combined with other data (e.g. weather, soil measurements, crop characteristics) and with remote sensing data to provide a larger picture of agricultural stress. Wolfert et al. (2017) emphasized on data-driven agriculture as an approach that positively shape the decision-making process due to different forms of agricultural information. However, there are certain considerations to be kept in mind like data interoperability, sensor quality, infrastructure, model accuracy, and model accessibility for the effective application of AI-based crop and soil monitoring. These are important things that affect the potential transfer of technologies to more commonplace agricultural use.

Livelihoods and the Climate's Resilience

Climate-resistant agriculture strives to maintain and/or improve agriculture's production and capacities, focusing on the ability to manage climatic risks, while preserving and/or building the resilience of agriculture and farmers. Digital technologies can do this too as an effective tool for disseminating timely information in relation to environmental condition, the health of crops and risks/concerns associated with the crop. Notably, agricultural automation and digital technology can drive improvements in efficiency, productivity and help contribute to a transition towards transforming agrifood systems (Food and Agriculture Organization [FAO] 2022). The problem can be solved with computer vision and deep learning, however, keeping track of it will help farmers warn themselves of potential threats and make timely decisions before the environmental crises or biological outbreaks are able to deal a major blow.

Using AI-driven agricultural technologies can also affect the economic stability of rural households by helping to make use of inputs more efficiently and minimizing unnecessary losses in production. Earlier and more effective detection of disease and pest can help make proper decisions in crop protection and better monitoring will help better use of water, fertilizer and other inputs. Javaid et al., (2023) highlighted that the use of artificial intelligence (AI) in agriculture is gaining importance and can improve productivity, resource utilization and decision-making in the area of precision agriculture. Low access to agriculture and climate risks coupled with low resource availability of the smallholder farmers makes this benefit more valuable. This perspective strongly believes that it is essential to incorporate computer vision and deep learning through a farmer-focused approach that respects farmer's needs, cost, training and reach. Improving capabilities of AI-based agriculture to not just protect the crop and soil but also contribute to climate resilience and sustainable livelihoods of communities can be achieved if the above dimensions are addressed.

Research Methodology

Research Design

The study used qualitative research design to explore the role of computer vision and deep learning in climate smart agriculture, covering areas of soil health, disease monitoring, and livelihood enhancement for the communities. Information was gathered through a cross-Sectional Survey Methodology from the agricultural stakeholders on their experiences, perception and the agriculture-related use of Artificial Intelligence. The design offered a structured framework to explore links between adoption of technologies and monitoring, protection of crops, management of resources and livelihood-resilience.

Population and Sample

The target population comprised of farmers, agricultural extension workers, agronomists and agricultural technology practitioners, who had prior knowledge or experience regarding DARTs. 300 respondents were chosen for the study. Farmers constituted the main group of respondents, as they are the groups most affected by challenges linked to climate changes, crop diseases and pests, as well as soil issues, while the agriculture hands-on professionals gave their technical views on how the use of AI could help them. The amount of observations obtained in this study was adequate for the description, reliability, correlation and regression study of the study variables.

Sampling Technique

A purposive sampling method was used to select interviewees with relevant agricultural skills/experiences of digital farming technology. The approach taken in recruiting farmers included agricultural communities, agricultural networks, and contacts with agricultural extension professionals, while agricultural professionals were identified based on their involvement in soil assessment, agricultural extension, agricultural technology, and/or crop management. Involved participants were those who gave informed consent and were knowledgeable about agricultural production and/or technology-powered farming.

Data Collection Procedure

Data collection techniques used in collecting primary data were a structured questionnaire answered by the selected respondents. There were sections on demographic information, applications of computer vision, applications of deep learning, soil health monitoring, crop protection, agricultural adaptation to climate change and livelihood outcomes of the community. There was a five-point Likert scale for measuring items, ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was administered both in a paper and online format to ensure that the questionnaire is accessible to all participants across various agricultural environment.

Data Analysis

Coded responses of the various questions in the questionnaire were analyzed using SPSS. Frequencies, percentages, means and standard deviations were computed for respondent characteristics and study variables. The associations between computer vision, deep learning, soil health, crop protection, climate resilience and community livelihood outcomes were analysed using Pearson's correlation analysis. The contribution of computer vision and deep learning to understanding agricultural outcomes that is predictive of climate resilience was investigated using multiple regression analysis. Variance inflation factor (VIF), tolerance, residual analysis and checking other diagnostic procedures were explored to gain insight into the regression assumptions.

Results and Analysis

Demographic Characteristics of Respondents

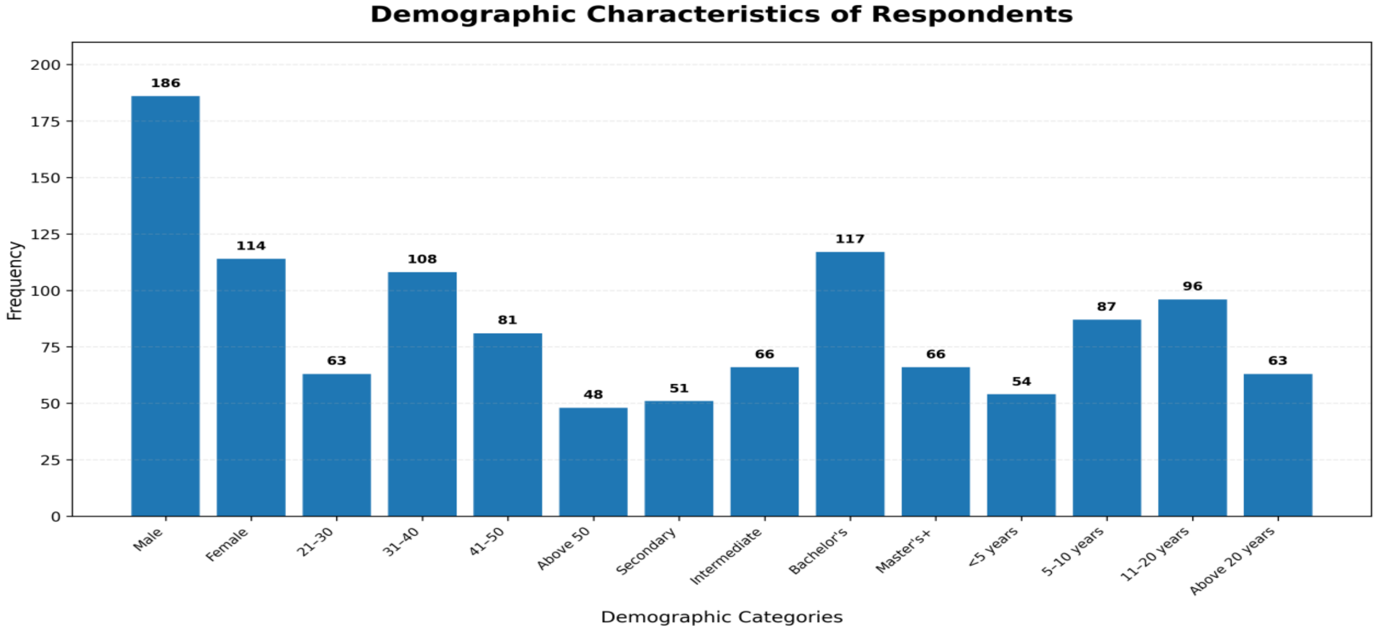
The demographic characteristics of the respondents were analyzed to provide a clear profile of the participants included in the study.

Table 1: *Demographic Characteristics of Respondents*

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	186	62.0
	Female	114	38.0
Age	21–30 years	63	21.0
	31–40 years	108	36.0
	41–50 years	81	27.0
	Above 50 years	48	16.0
Education	Secondary	51	17.0
	Intermediate	66	22.0
	Bachelor's	117	39.0
	Master's or above	66	22.0
Agricultural Experience	Below 5 years	54	18.0
	5–10 years	87	29.0
	11–20 years	96	32.0
	Above 20 years	63	21.0

The results showed that males represented 62.0% of the respondents, while females represented 38.0%. The comparatively higher percentage of male respondents in the selected agricultural activities, resulted in higher representation of men. As far as age is concerned, respondents were aged between 31 and 40 years which made 36.0% of the sample while respondents between the age 41 and 50 years accounted for 27.0%. The age group of 21-30 years represented 21.0% and above 50 years represented 16.0%. Results of the educational characteristics revealed that those who have bachelor's degree were the most prevalent educational group, constituting 39.0% of the participants. Intermediate education accounted for 22.0% and master's or higher accounted for 22.0% of the respondents. The 11–20 years of experience group had the largest percentage of respondents at 32.0%, followed by 29.0% of those with 5–10 years of experience in the profession. In educational experience, 21.0% of the participants had more than 20 years' experience and 18.0% of the participants had less than five-year experience in agriculture.

Figure 1: *Demographic Characteristics of Respondents*



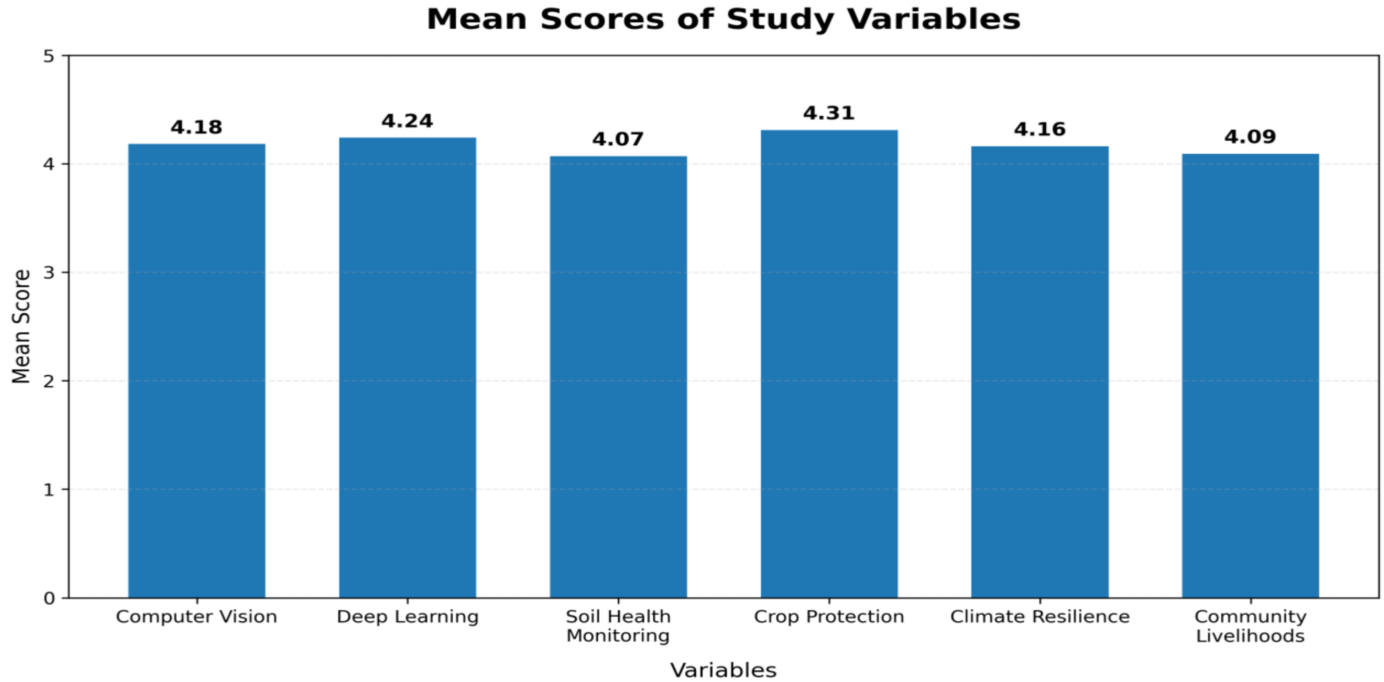
Descriptive Results of Computer Vision, Deep Learning, Soil Health, and Crop Protection

Table 2: *Descriptive Statistics of the Study Variables*

Variable	N	Mean	Std. Deviation
Computer Vision	300	4.18	0.62
Deep Learning	300	4.24	0.59
Soil Health Monitoring	300	4.07	0.67
Crop Protection	300	4.31	0.55
Climate Resilience	300	4.16	0.61
Community Livelihoods	300	4.09	0.64

Table 1, in general, showed that there was a high level of agreement for all study variables. The mean score of 4.18 obtained in the computer vision category was relatively high and the standard deviation was low of 0.62 indicating that the participants were generally positive towards computer vision as a good technology for monitoring agriculture. Deep learning gave a slightly higher mean of 4.24 (SD = 0.59) showing adequate perception of its ability to sense the agricultural situation and aid decision making. The highest mean score among the 6 variables was obtained in crop protection with a score of 4.31 with a standard deviation of 0.55. But this outcome found that the most useful use of AI-assisting technologies was crop disease detection, pest attack detection and other means used to measure plants' stress. The scores were also high for deep learning (4.24) indicating that automatic image classification and pattern recognition can be a tool to enable early detection of farming issues. The mean score for soil health monitoring was 4.07 (SD = 0.67) indicating above the midpoint and positive perceptions about technology for soil monitoring. The mean score of climate resilience was 4.16 (SD = 0.61), and community livelihoods 4.09 (SD = 0.64). These findings show that in general, the respondents equated computer vision and deep learning to better abilities in facing up to problems in agriculture and the environment.

Figure 2. *Descriptive Statistics of the Study Variables*



Correlation Analysis

Pearson correlation analysis was performed to examine the direction and strength of relationships among the study variables.

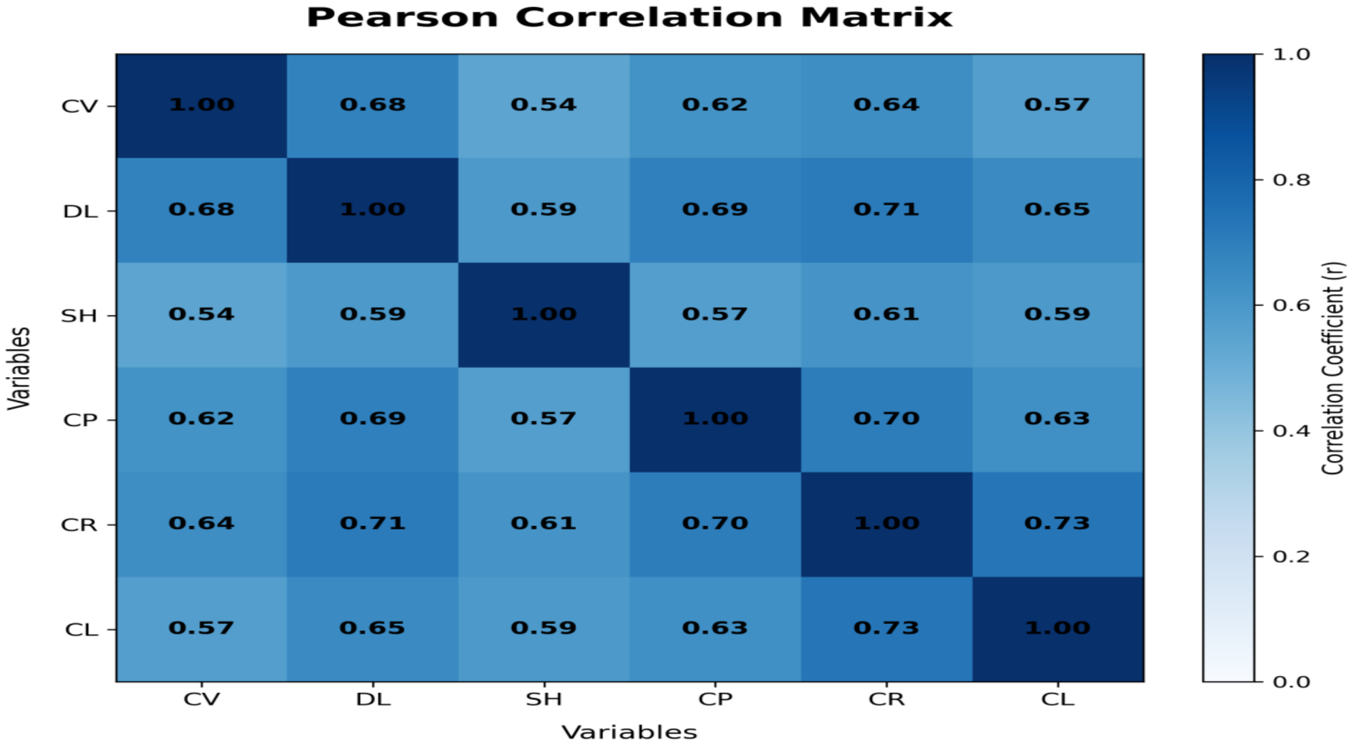
Table 3: *Pearson Correlation Matrix*

Variable	CV	DL	SH	CP	CR	CL
Computer Vision (CV)	1					
Deep Learning (DL)	.68	1				
Soil Health (SH)	.54	.59	1			
Crop Protection (CP)	.62	.69	.57	1		
Climate Resilience (CR)	.64	.71	.61	.70	1	
Community Livelihoods (CL)	.57	.65	.59	.63	.73	1

Note: *p < 0.01.*

The positive correlation of all major variables was obtained from the correlation results. There is positive correlation between PCV and DL (r = .68, p < .01); therefore, those who reported higher levels of PCV also reported higher levels of DL. Computer vision also was positively correlated with soil health (r = .54), crop protection (r = .62), climate resilience (r = .64) and community livelihood (r = .57). The findings indicated stronger relationships of the agricultural outcome variables with deep learning. It was seen to have a correlation of r = .69 and with crop protection, r = .71 respectively with climate resilience. The eagerness regarding connection to the community livelihoods was additionally positive and relative high (r = .65). Climate resilience had the highest correlation with the community's livelihoods (r = .73, p < .01). Climate resilience was highly associated with crop protection, at a value of r = .70 and p < .01. All the correlations were positive and showed that the more the technology was used, the better were the agricultural and livelihood results.

Figure 3. *Pearson Correlation Matrix*



Multiple Regression Analysis

Multiple regression analysis was conducted to examine whether computer vision and deep learning significantly predicted climate resilience.

Table 4: *Model Summary*

Model	R	R^2	Adjusted R^2	Std. Error of Estimate
1	0.79	0.62	0.61	0.38

The model demonstrated a strong combined relationship between Computer Vision, Deep Learning and Climate Resilience with an R value of 0.79. The two independent variables accounted for 62.0% of the variation in climate resilience with an R2 of 0.62. The model could explain a significant part of the variance even after the number of predictor variables was taken into account, with the adjusted R^2 value being 0.61.

Figure 4: *Model Summary*

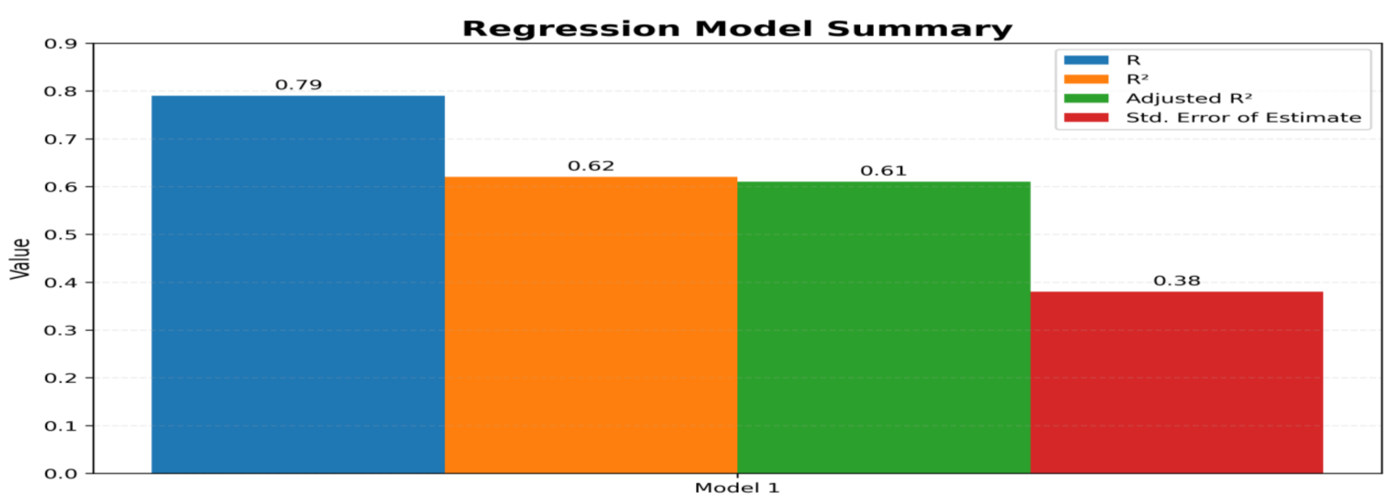
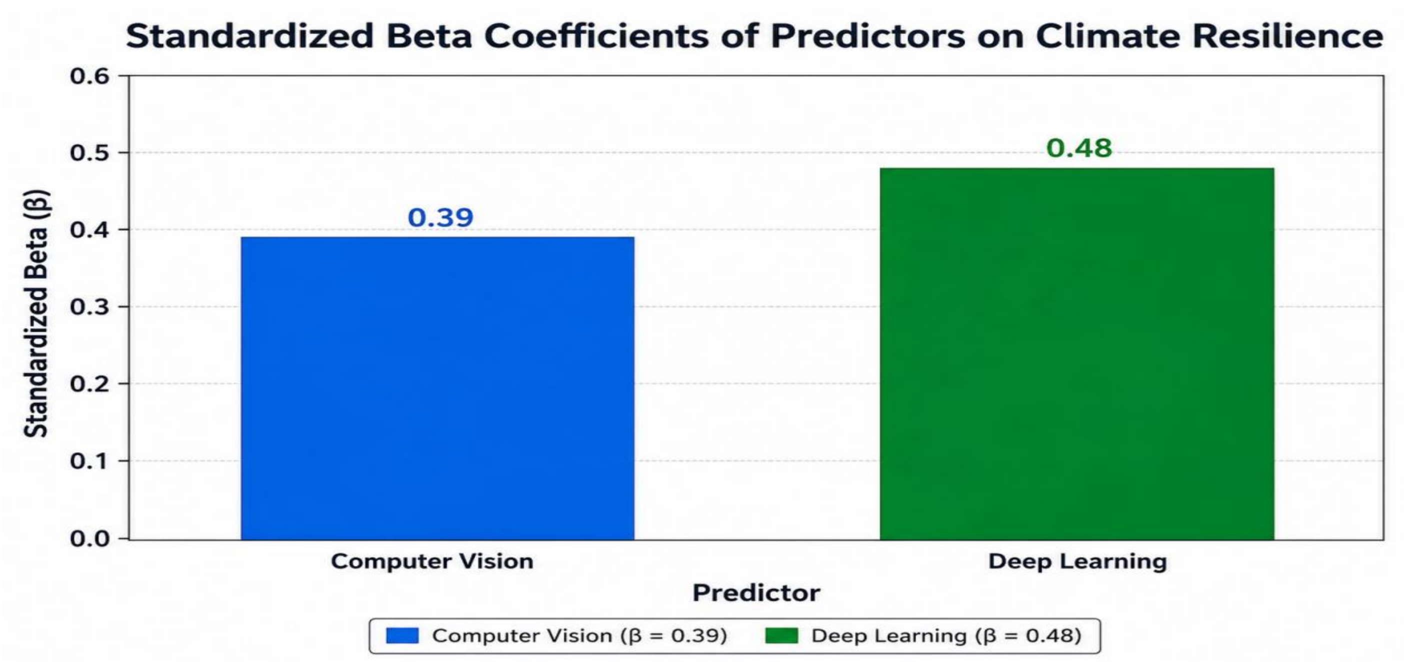


Table 5: *Regression Coefficients*

Predictor	B	Std. Error	Beta (β)	t	p-value	VIF
Constant	0.91	0.21	—	4.33	<0.001	—
Computer Vision	0.38	0.06	0.39	6.33	<0.001	1.72
Deep Learning	0.47	0.06	0.48	7.67	<0.001	1.72

The coefficient results revealed that computer vision is significant in predicting climate resilience ($B = 0.38$, $\beta = 0.39$, $t = 6.33$, $p < 0.001$). Positive coefficient suggested an availability of an increasing number of computer vision application with an increasing climate-resilience score. The other predictor contributed to a standardized beta of 0.39, which was a moderate contribution when compared to the other predictor. Furthermore, deep learning was found to have a positive and statistically significant association ($B = 0.47$, $\beta = 0.48$, $t = 7.67$, $p < 0.001$) with climate resilience. The standardized coefficient was higher than the computer vision coefficient, suggesting a relatively high contribution towards climate resilience. The conclusion indicated that for the technology-supported climate adaptation in particular, automated pattern recognitions, classifications, and predictions as key strengths of deep learning were significant. Both the predictors had acceptable level of multicollinearity with the VIF value 1.72 respectively. The results are, therefore, presented as evidence that the two predictors could be understood together with no serious indication of a high degree of redundancy between them.

Figure 5. *Regression Coefficients*



Discussion

The literature suggests that computer visions and deep learning will drive additional shifts in how farms and agricultural fields will be monitored, and processes enabled to process the visual data streaming from crops, fields and environment. The importance of their value goes beyond just image classification as other AI systems can aid in the quicker identification of agricultural conditions, thereby helping in informed farm management. The capabilities are particularly critical for climate resilient actions in Agriculture, where timely information can support farmers' adaptation activities to the changing climate. AI-powered tools for greater precision in monitoring, decision making, and automation can help with precision agriculture as noted by Benos et al. (2021).

In another crucial area, soil health, AI can be used to complement the standard assessments used in farming. The visible soil and vegetation stress, moisture status, other parameters can provide valuable farm management information and can be complemented with digital soil image analysis. Data derived from remote sensing combined with soil data, weather data and crop data can be used in the process of more detailed evaluation with the help of machine learning techniques. Padarian et al. (2019) highlighted the opportunities that deep learning provides to create more sophisticated digital soil mapping methods, whereby many complex spatial and environmental relationships are dealt with. These can contribute to the sustainable management of soils in the long term and to the sustainable production in agriculture.

Crop protection is considered one of the most promising for computer vision as plant diseases, pests and physiologic stresses often create recognizable visual patterns. The recognition system could leverage AI technology, thus helping agricultural experts and farmers to gain the benefits of timely threat recognition and specific actions that allow them to make informed decisions. One approach is to eliminate the requirement for periodic manual checks, and broaden the capacity to monitor crop status. Singh et al. (2020), however, noted the potential application of deep learning, computer vision in plant disease detection and diagnosis and the necessity of having various plant datasets and field testing for its successful application in agriculture.

AI's impact on agricultural resilience also hinges on the success of technology systems in integrating into current fields and systems of practice and decision-making. Digital tools can provide much valuable information but farmers' need focuses on the capability to access, connect and receive technical support, as well as sufficient confidence in the accuracy of automated recommendations. The introduction of digitalization to agriculture is therefore social as well as model based. While digital agriculture has the potential to offer opportunities for greater efficiency and sustainability, it can also create access, skills, data ownership, and, as noted earlier, differential technological participation issues (Rotz et al., 2019). These issues are particularly important in the context of bringing the technology of the artificial intelligent system to the resource base small communities (rural areas).

Agricultural technology is also good for community's livelihoods, optimizing agricultural production and conserving agricultural resources, managing agricultural risks and facilitating access to agricultural information. Improvements in sustainable livelihoods, however, depends on a technological environment that is inclusive so that small farmers can obtain affordable tools and learn their use so they can be effective. Therefore, facilitative approaches should be used to implement digital agriculture, considering agricultural knowledge and socio-economic aspects. For farmer-centred digital transformation, collaboration between farmers, technology developers, researchers and institutions was key, as Eastwood et al (2019) argued. This can contribute to making computer vision and deep learning relevant and available for the support of resilient farming systems.

Conclusion

The study has suggested the useful role of artificial intelligence, specifically the computer vision and deep learning methods to increase climate resilient agriculture. Some of them allowed for the connection of automated image analysis, efficient pattern recognition, crop observation, soil evaluation and decision support for agricultural control. Use of their products could help identify stresses in crops, disease, pest and environmental conditions, and help to manage resources sustainably in an efficient manner. The study highlighted that the role of AI is not only in the production but also in the improved situation of monitoring and decision-making processes, which can contribute to the capacity to adapt and to foster sustainable rural development.

Recommendations

Agricultural institutions need to promote and push computer vision and deep learning skills to farmers in an ethical and responsible way through farmer education, technical assistance, farmer demonstrations and accessible digital platforms. Reliable internet connectivity and cost-effective imaging devices and agricultural sensors, and locally relevant artificial intelligence systems seen more favorably, particularly in rural areas and with resource-poor systems. Agricultural data and agricultural technologies should be created that represent various degrees of within-farm practice, farm environments, disease types, climate types and soil types; to improve the model's reliability. Cooperation from farming communities, Agricultural Extension workers, Universities, and Technology developers and policy makers can help provide assistance to local systems needing practical solutions to the local agricultural needs. As well, data privacy and transparency, explainable models and fair access to the service will continue to be significant factors to check in at implementation time.

Future Directions

More effort should be devoted to using bigger and broader (geographically) datasets to further enrich their ability to model and generalize agricultural AI models. The impacts of AI-based intervention can be evaluated over a large spawning point-to-soil, from soil health and crop productivity to resource efficiency, climate adaptation through reduced labour requirements, and impact of livelihoods of the households. Combining the Computer Vision technology, achieved by using Drones, satellite images, sensors of the IoT, weather data and soil monitoring technology, can realize the following development of agricultural decision support systems. Further opportunities exist for the incorporation of visual, environmental and socioeconomic information by advanced models, like transformer-based models and multimodal AI. The opportunities and barriers related to the affordability, usability and digital literacy of AI technologies must be explored, as must be technological advancements for inclusive and sustainable climate resilient agriculture.

Conflict of Interest

The authors showed no conflict of interest.

Funding

The authors did not mention any funding for this research.

References

Benos, L., Tagarakis, A. C., Dolias, G., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*, *21*(11), 3758. https://doi.org/10.3390/s21113758

Eastwood, C., Ayre, M., Nettle, R., & Dela Rue, B. (2019). Making sense in the cloud: Farm advisory services in a digital environment. *NJAS: Wageningen Journal of Life Sciences*, *90–91*, 100298. https://doi.org/10.1016/j.njas.2019.100298

FAO. (2021). *The state of food and agriculture 2021: Making agrifood systems more resilient to shocks and stresses*. Food and Agriculture Organization of the United Nations.

FAO. (2022). *The state of food and agriculture 2022: Leveraging automation in agriculture for transforming agrifood systems*. Food and Agriculture Organization of the United Nations.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

IPCC. (2022). *Climate change 2022: Impacts, adaptation and vulnerability*. Cambridge University Press.

Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Khan, S. (2023). Unlocking the opportunities through artificial intelligence in agriculture. *Artificial Intelligence in Agriculture, 7*, 20–35. https://doi.org/10.1016/j.aiia.2022.12.001

Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Khan, S. (2023). Unlocking the opportunities through artificial intelligence in agriculture. *Artificial Intelligence in Agriculture, 7*, 20–35. https://doi.org/10.1016/j.aiia.2022.12.001

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and future research directions. *NJAS: Wageningen Journal of Life Sciences, 90–91*, 100315. https://doi.org/10.1016/j.njas.2019.100315

Koirala, A., Walsh, K. B., Wang, Z., & McCarthy, C. (2019). Deep learning—Method overview and review of use for fruit detection and yield estimation. *Computers and Electronics in Agriculture, 162*, 219–234. https://doi.org/10.1016/j.compag.2019.04.017

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 2674. https://doi.org/10.3390/s18082674

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science, 7*, 1419. https://doi.org/10.3389/fpls.2016.01419

Mulla, D. J. (2013). Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

Padarian, J., Minasny, B., & McBratney, A. B. (2019). Using deep learning for digital soil mapping. *SOIL, 5*(1), 79–89. https://doi.org/10.5194/soil-5-79-2019

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., LeBlanc, J., Martin, R., Neufeld, H. T., Nixon, A., Pant, L., Shalla, V., & Fraser, E. D. G. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping the future of farming. *Canadian Journal of Communication, 44*(1), 1–19. https://doi.org/10.22230/cjc.2019v44n1a3429

Singh, A. K., Ganapathysubramanian, B., Singh, A. K., & Sarkar, S. (2020). Deep learning for plant stress phenotyping: Trends and future perspectives. *Trends in Plant Science*, *25*(9), 883–898. https://doi.org/10.1016/j.tplants.2020.03.004

Wadoux, A. M. J.-C., Padarian, J., & Minasny, B. (2019). Multi-source data integration for soil mapping using deep learning. *SOIL*, *5*(1), 107–119. https://doi.org/10.5194/soil-5-107-2019

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming—A review. *Agricultural Systems*, *153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023.