AGRICULTURAL SCIENCE AND TECHNOLOGY, VOL. 15, No 4, pp 12-22, 2023
Published by Faculty of Agriculture, Trakia University, Bulgaria
ISSN 1313-8820 (print)
ISSN 1314-412X (online)
http://www.agriscitech.eu
DOI: 10.15547/ast.2023.04.033

Digital image processing applications in agriculture with a machine learning approach

Suraiya Yasmin[1*], Masum Billah[1]

[1]Department of Computer Science and Information Technology, Faculty of Agriculture, Bangabandhu Sheikh Mujibur Rahman Agricultural University, Gazipur-1706, Dhaka, Bangladesh

(Manuscript received 6 February 2023; accepted for publication 1 December 2023)

Abstract. *Digital image processing involves the manipulation of images by digital means, and its use has been increasing exponentially in recent decades. It is applied in a diverse range of fields including medicine, remote sensing, robotic vision, and audiovisual processing. Image processing technologies are widely used as a proficient tool in the agriculture sector. The combination of digital image processing and machine learning not only provides new insights into crop health and environmental circumstances, but also helps farmers reach timely and precise decisions. Using machine learning methods, this study examines digital image processing applications in agriculture, focusing on plant disease identification, fruit quality evaluation, weed detection, yield mapping, and robotic harvesting, to other issues. In essence, this study integrates existing knowledge at the interface of digital image processing, machine learning, and agriculture, providing insights into a promising and growing topic with significant implications for sustainable and resilient food production.*

Keywords: Image processing, computer vision, plant disease, robotic harvesting, machine learning, smart farming, deep learning, artificial neural network

Introduction

The quality of agricultural production is crucial for the economic growth of any nation. Traditional methods of producing high-quality agricultural products are labor-intensive, time-consuming, and costly, particularly in developing countries (Ganatra and Palet, 2018). The agriculture sector has started to work with innovative techniques like image processing, machine learning, computer vision, remote sensing, geographical information systems, etc. By using those technologies, it will be possible to produce informative and supportive results that are helpful for farmers, agro-based industries, and marketers as well (Prabha and Kumar, 2014). Among these challenges is disease detection, a particularly daunting task. Notably, many diseases affect plant leaves and stems, causing significant damage. Researchers found that plant diseases cause heavy crop losses, which are equivalent to several billion dollars annually. Historically, plant diseases have had devastating effects, such as the late blight disease of potatoes, which contributed to the Irish famine between 1845 and 1847 (Patil and Kumar, 2011).

In the traditional approach, farmers relied on expert's eye observation on affected plant samples and tried to cure the plant diseases based on the expert's suggestions, which was a time-consuming and more expensive method. Furthermore, expert solutions can be impractical for farmers who must inspect large areas, as this requires a sizable team for continuous monitoring. Additionally, the communication barrier between farmers and experts can hinder effective disease management. Nevertheless, timely detection and classification of plant diseases are crucial for informed decision-making. That's why machine learning image processing techniques are used for fast, automatic, spontaneous, and accurate detection of plant leaf diseases. Image segmentation methods, for instance, are used to quantify the affected areas on plant leaves by discerning color differences (Singh and Misra, 2017).

Weeds, undesirable plants in farming areas, pose another significant challenge. Many researchers have developed various image processing methods for weed control (Vibhute and Bodhe, 2012). Weed detection techniques use image processing algorithms such as edge detection, color detection, wavelet classification, fuzzy logic, etc. Nondestructive quality evaluation of fruit is important for the agricultural food industry. Traditional fruit grading is performed primarily by naked eye observation, but the image processing method is used for automated fruit size grading to provide accurate, reliable, consistent, and quantitative information which is not possible by employing human graders (Rupali and Patil, 2013). Nowadays, image processing techniques include image segmentation, morphological image processing for shape analysis, texture analysis, noise elimination, 3D vision, pattern recognition, and feature extraction, which are used for fruit grading and quality management. However, robotics and machine vision technologies are used with image processing for harvesting fruits and vegetables. Besides irrigation, water stress, yield, fertilizer and pesticides are the major concerns in the agriculture sector. Analyzing these problems requires a substantial amount of expertise. Image processing tools and techniques offer potential solutions for reducing errors and costs, thereby contributing to economically sustainable agriculture (Calafell, 2014). This paper aims to elucidate various machine learning and image processing tools applicable in agriculture and to inspire further research in smart farming.

Digital Image processing application for plant disease detection

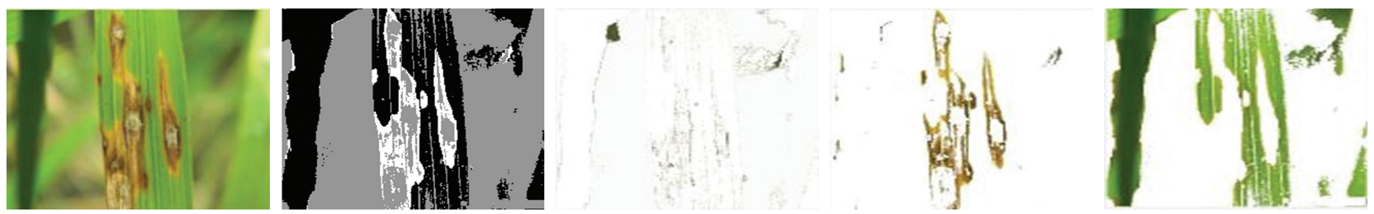
Al-Hiary et al. (2011) proposed an algorithm for plant leaf disease detection and classification. To carry out the work, the step-by-step process of the image segmentation and recognition was illustrated in that algorithm. In the early step, the RGB images were considered, and the real samples of disease-affected leaves were observed. There was a major difference between greasy spot diseases, which include early scorch, cottony mold, ashen mold, and late scorch diseases, in terms of color and texture. These differences in spotted leaves observed with the human eye may justify the misclassifications. The researchers divided the total processes into four phases. In phase 1, the K-means clustering technique was used for image segmentation and infected objects were determined. In phase 2, mostly green-colored pixels were identified, and then the Otsu's method was applied. In phase 3, the color co-occurrence method was used to extract features. Then they developed the color co-occurrence texture analysis method through the use of Spatial Gray-level Dependence Matrices (SGDMs). In phase 4, neural networks were used in the automatic detection of leaf diseases due to its well-known technique as a successful classifier for many real-world applications. Furthermore, two major processes, training and validation, were utilized in the neural network technique.

Sun et al. (2018) proposed multiple linear regression models which represented a new image recognition system to identify whether the plant leaves were affected by disease or not. They proposed a histogram segmentation method for the accurate and automatic calculation of image threshold. To improve accuracy, they combined regional growing techniques and true color image processing with this system. Kothawale et al. (2018) used a Support Vector Machine (SVM) classifier in the detection and classification of grape leaf diseases. In their study, 90 grape leaf images were used for training and testing purposes. Among them, 70 images were for the training phase and 20 images were for the testing phase. The SVM classifier classifies the input images into healthy as well as disease-affected leaves. Various image processing techniques for plant disease detection are illustrated in Figures 1 and 2. The digital image samples of plant leaves were collected from the environment and image preprocessing was done as shown in Figures 1 (a, b) to avoid the background noise, which may severely affect the main results. In Figure 2 (b), an RGB image of a rice leaf sample was converted to binary images. This transformation was important because it would be used as input images in the segmentation stage where K-means clustering was to be used for disease classification. In Figure 2 (c), the threshold image was identified by applying Otsu's method. In Figure 2 (d), segmented leaf images were classified into disease-affected areas and normal areas of the leaves were separated as depicted in Figure 2 (e).

*email: suraiya@bsmrau.edu.bd

(a) (b)

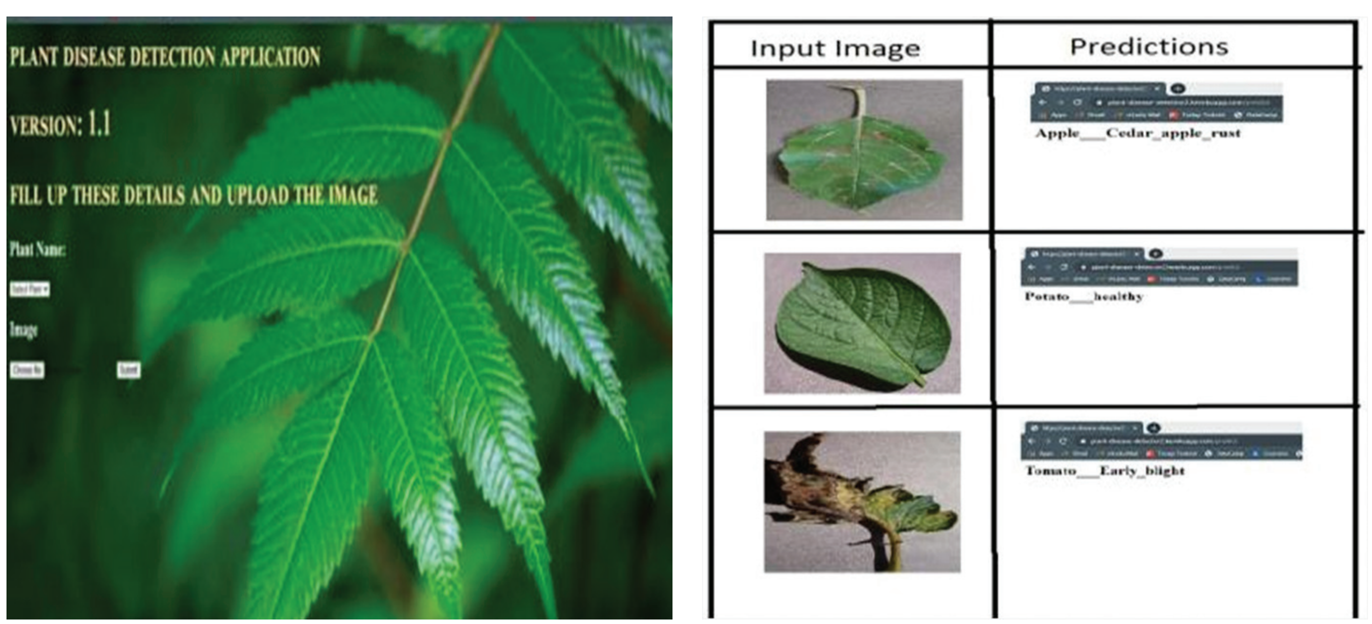
Figure 1. (a) normal rice leaf, (b) disease affected rice leaf



(a) (b) (c) (d) (e)

Figure 2. (a) Input image, (b) Color transformation (conversion of RGB images to binary image), (c) threshold identification, (d) Disease affected area detection, (e) Normal leaf area detection

Kulkarni et al. (2021) analyzed various image parameters or features to identify several types of plant leaf diseases to achieve the best accuracy. They applied statistical machine learning and digital image processing algorithms for automatic disease detection of plant leaves. To extract the texture features, they applied the GLCM method of computer vision technology. They developed a Flask-based web application and deployed it on Heroku, a cloud platform offering free hosting options. In agricultural fields, an intelligent robotic vehicle equipped with a high-end processor is used for real-time plant disease detection and for spreading fertilizer. Farmers may require expert advice when they are unable to identify plant diseases. Farmers can upload images of diseased plants to the website, which then provides recommendations for fertilizers based on the detected diseases as shown in Figure 3.



(a) (b)

Figure 3. a) Homepage of deployed web application. b) Input images and outputs generated by system

Digital Image processing application for fruit quality evaluation

Bargava and Bansal (2021) applied different types of machine learning image processing techniques to inspect the quality of fruits and vegetables. For example, image acquisition, preprocessing, image segmentation, feature extraction, and classification techniques were used to implement their proposed work. According to this literature, the fruit and vegetable images were captured from one direction by an RGB color camera. The traditional computer vision system, as shown in Figure 4, was at ease to use to inspect many characteristics such as texture, shape, color, size, defects, etc. automatically. They investigated different picture segmentation approaches, including thresholding and k-means clustering algorithms, which were employed for segmentation and fungal identification. However, the feature extraction method was considered in which the feature vector defines the object shape uniquely and precisely. The features of an image like color, texture, shape, and size were considered using CIELAB color space, and then a classification algorithm was applied. The powerful classification algorithm Support Vector Machine (SVM) was used to classify both linear and non-linear data.

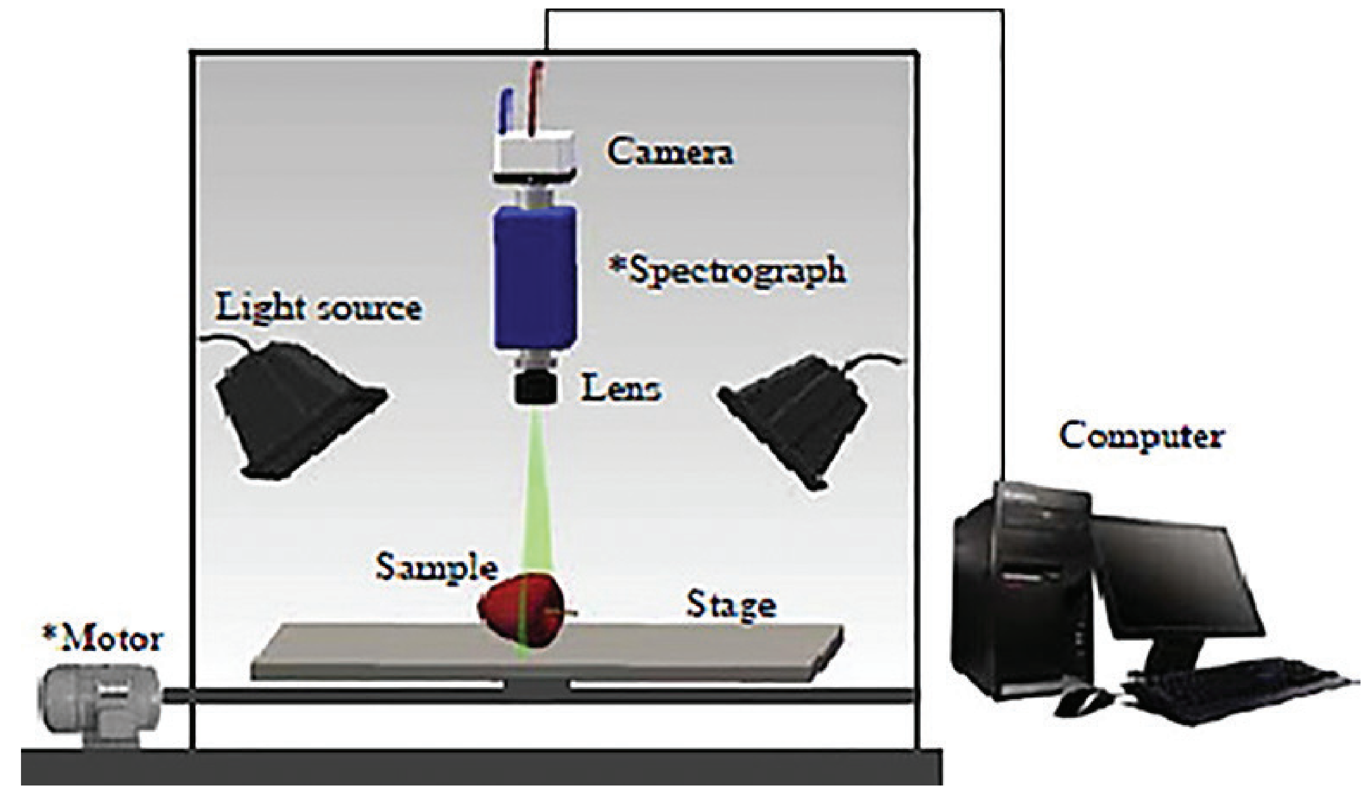
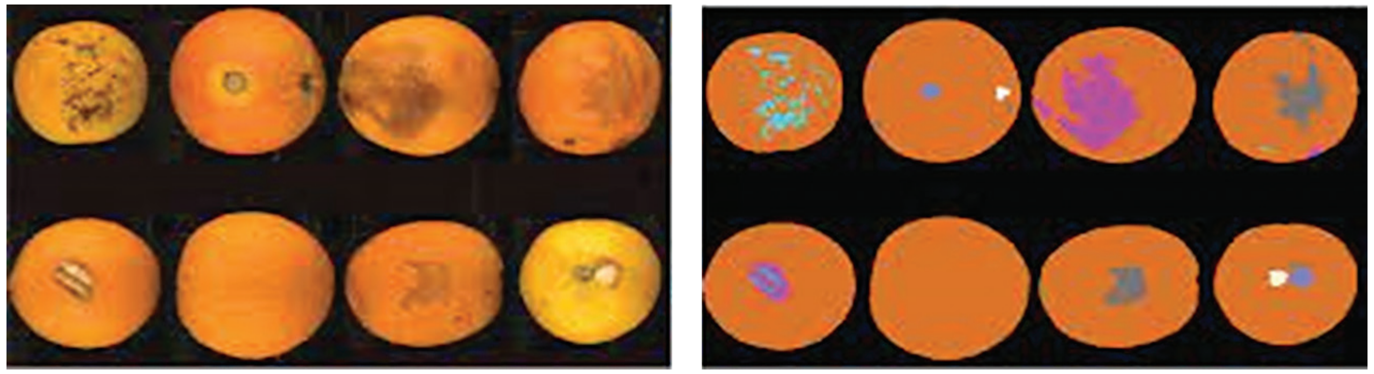


Figure 4. Computer Vision system for fruit quality inspection

The above Figure represents a typical computer vision system, which consists of two main components, which are image acquisition and image analysis. Image acquisition consists of an image capture device and illumination. Image analysis comprises an image capture board (digitizer or frame grabber) and analysis software. The light systems are structured as front and back lighting for the analysis of fruits as well as vegetables. Over the past few years, both hyper spectral and multispectral computer vision systems have been used as a powerful tool for the external quality assessment of fruits and vegetables automatically and accurately (Narendra and Hareesha, 2010).

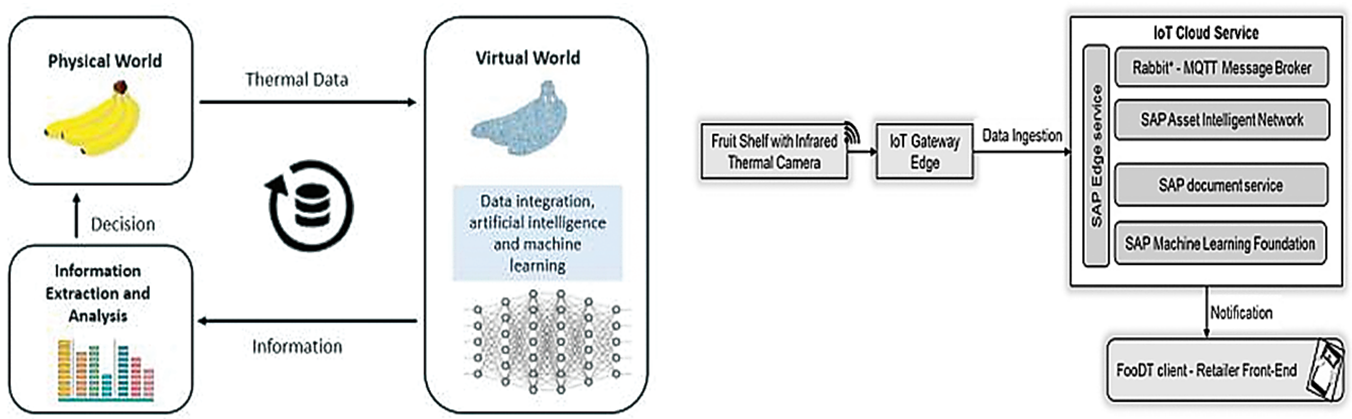
Cubero et al. (2015) developed an efficient computer vision system which was to be mounted on an agricultural vehicle. The aim of their research was to monitor the field and examine the quality of the product during harvesting. They escalated the whole computer vision system on the agricultural vehicle, which assists in citrus fruit harvesting. This system was also tested in the field for inspecting the color, size, and skin defects of the harvested fruits at a rate of eight fruits per second and sorting the fruits into three outlets which is illustrated in the following Figure 5.



(a) (b)

Figure 5. a) Images of orange with several defects b) Segmented images represent the defects found

Melesse et al. (2022) created a digital twin of banana fruit to monitor its quality changes throughout storage with a machine learning technique. They utilized a thermal camera to detect surface and internal changes in fruits during storage, aiding in data acquisition. In this study, after building the dataset of four classes of thermal data, the training of the model was accomplished using intelligent technologies from SAP (System Application and Products). They applied a deep convolutional neural network model to monitor the fruit status by which 99% prediction accuracy was achieved. The application of thermal imaging methods can be used as a data source to generate a machine learning-based digital twin of fruit which can minimize waste in the food supply chain. They also proposed a methodology for creating a digital twin of fruit using a thermal camera as a data source. Their proposed solution helps retailers and other stakeholders involved in the fruit supply network which is shown in Figure 6.

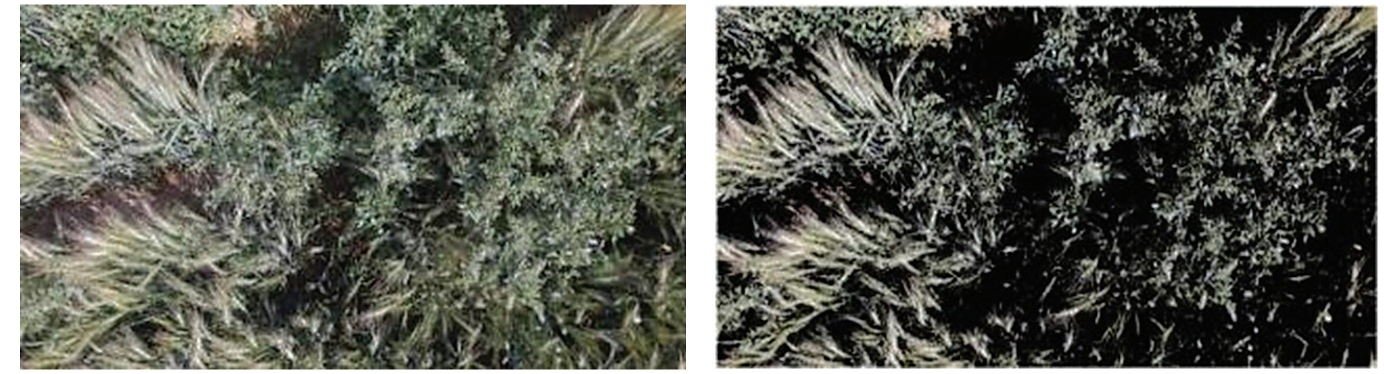


(a) (b)

Figure 6. a) Digital twin of fruit produce. b) The architecture of the proposed solution

Digital Image processing application for weed detection

Sarmad and Imran (2018) selected a wheat field to detect both weeds and wheat. The area of the wheat crop was 5 acres. A certain area of land was considered for the research study. Multiple images were taken at different times to analyze the growth of wheat and weed. The primary goal of this research was to detect barren land in the alert area of the wheat crop field. The main focus of the research was to detect the difference between wheat and weed. Their research was done at the time when the percentage of the crop growth was at 70. At this stage, the team encountered the challenge of distinguishing between weeds and wheat, as both were green. When the color of the wheat changed to yellow, they applied image processing techniques to notice both the weed and the wheat. The total experiment was divided into three segments with respect to crop growth. To carry out the work, images were acquired by using a drone, and the image data was fed into MATLAB for preprocessing. In the first segment, the researchers determined the barren land by applying edge detection theory when the crop was around 50% matured. In segment 2, they identified both weed and wheat when the crop was grown around 75% as well as the color of weed and wheat was alike (the green color) through the background subtraction method. In the third phase, the crop was 85% mature at that time as shown in Figure 7.



(a) (b)

Figure 7. Detection of both weed and wheat when the crop is matured around 85%. (a) Input image with both weeds and wheat (b) output image where the black color areas are weeds

Sandeep Kumar et al. (2018) discussed weed classification with the combination of image processing and convolution neural network (CNN). Images of crops and weeds were segmented and classified using CNN. Their experimental work used the RGB weed detection database which comprises 39 images of carrot plants along with weed. These images were segmented and fed to CNN for classification. This system showed an effective and reliable classification of 95% with a reduced misclassification rate.

Bavithra and Lavanya (2019) proposed a system that is a robot that identifies the weeds, differentiates them and also removes them from crops without any harm. To carry out the work, they used image processing techniques to detect and remove the weeds from a crop in the field. This may help farmers to maintain their crops and optimize the use of resources single-handedly. The weedicide spray robot implemented a method which was used to detect weed with image processing. This work was achieved by giving input images of weed blocks to the system and similar blocks in the image were colored differently for the robot to identify the weeds. The robot receives data and control signals wirelessly, enabling its sprayer to target only the weeds with herbicides. The experimental results for weed detection in various growing conditions are shown in Figure 8, which follows.

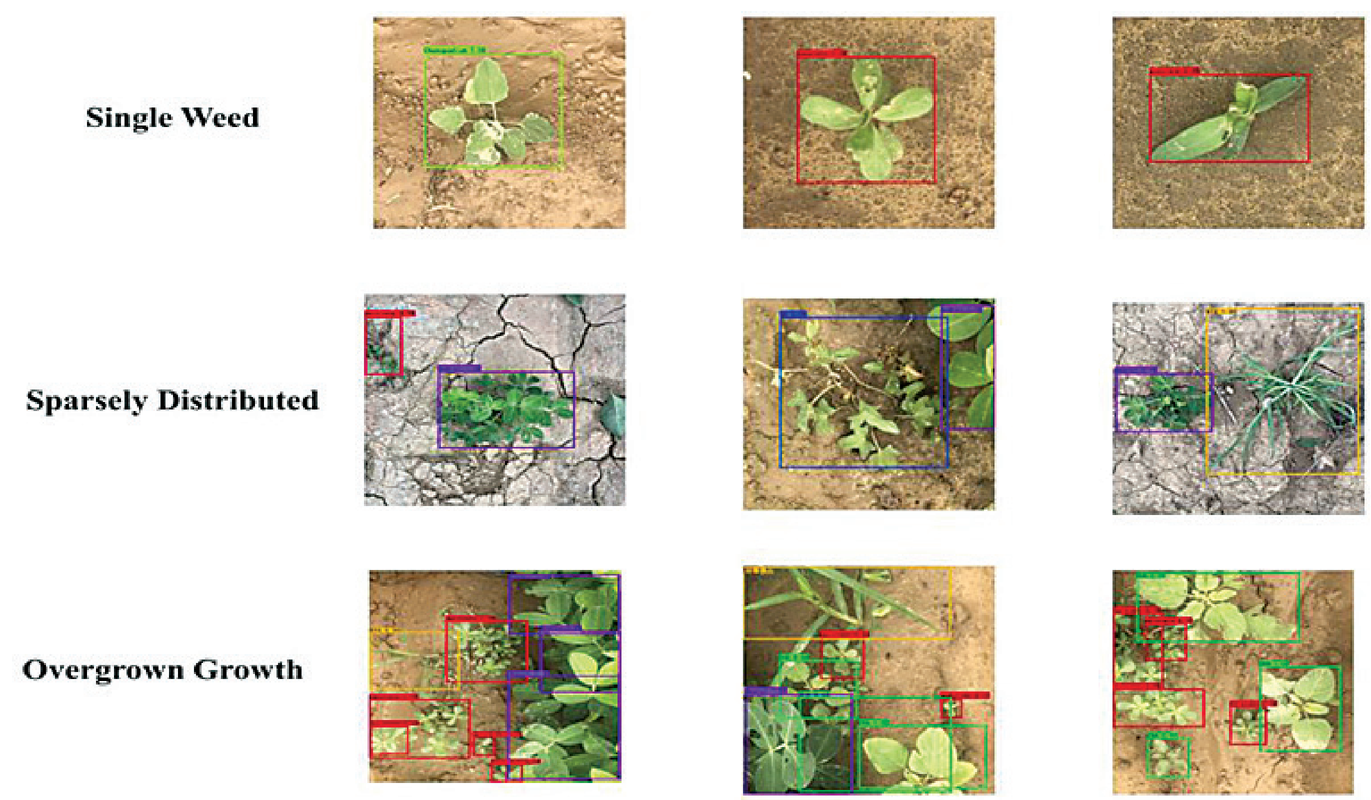
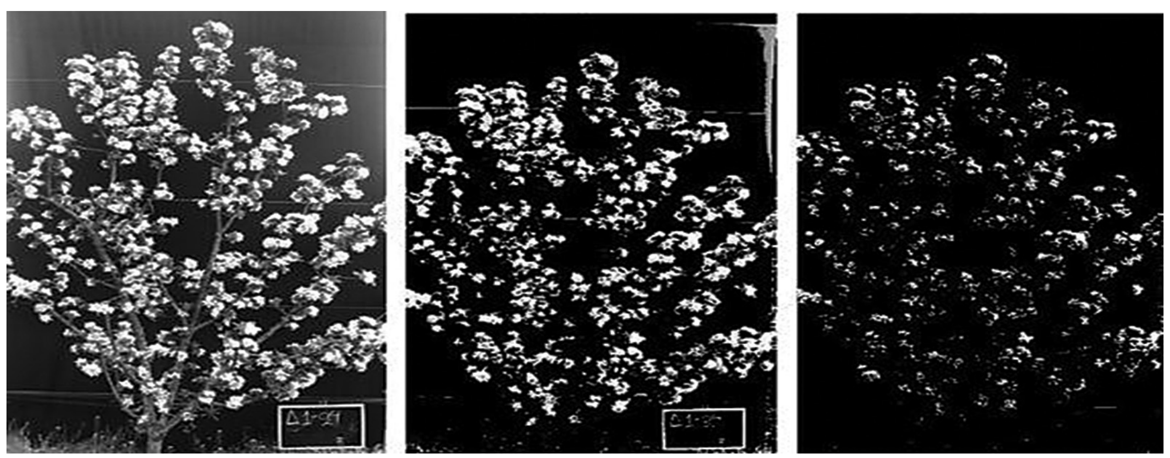


Figure 8. The experimental results in terms of weed detection under different growing condition

Digital Image processing application for yield mapping

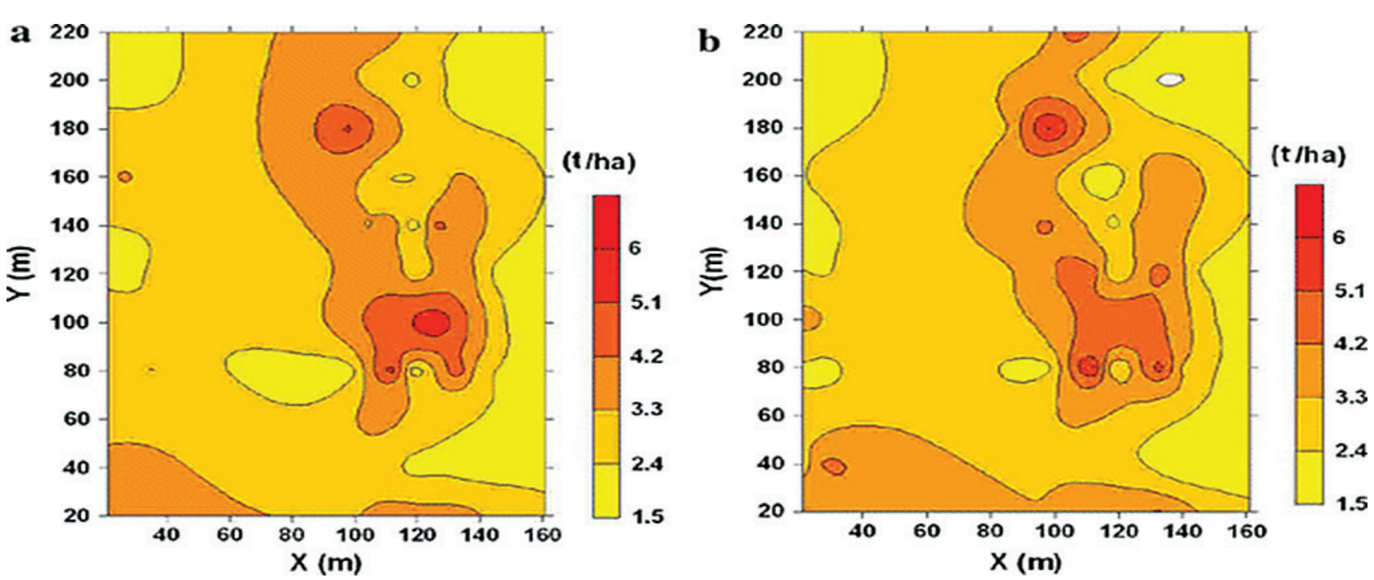
Schwalbert et al. (2020) presented a new model for in-season soybean yield forecasting in southern Brazil. To carry out the work, they compared the performance of three different algorithms including multivariate linear regression, random forest, and neural networks as well as assessed how early in the soybean growing season, this method was able to predict yield with sound accuracy. Satellite and weather data were screened using a non-crop-specific layer with field boundaries obtained, which was mandatory for all farmers in Brazil. This research showed the benefits of integrating statistical techniques, remote sensing, and weather information with field survey data in order to perform more reliable in-season soybean yield forecasts.

Aggelopoulou et al. (2010) carried out their research work in a commercial apple orchard in central Greece. Firstly, they collected the data about the measured yield of the trees and image samples representing the flower distribution. After collecting data, they developed an image processing algorithm which predicts the tree yield by analyzing the texture of images of the apple tree at full bloom. For the evaluation of algorithm to estimate the apple yield 113 images were considered. A case study scenario was presented where 60 of them represented a set of sample images to develop the model while the remaining 53 images represented a set of images used to validate apple yield estimation. They wanted to make sure that this estimation of expected production at bloom time will be useful for farmers, post-harvest industry and regional market planning. Figures 9 and 10 represent the colored and binary image threshold and the predicted yield map, respectively.



(a) (b) **(c)**

Figure 9. Sample images: a) colored b) binary image threshold 150 c) binary image threshold 250



(a) (b)

Figure 10. a) Yield maps for measured yield b) Yield maps for predicted yield

Qian et al. (2018) proposed a distribution outline comprised of image acquisition of fruits, yield prediction, data processing and model calculation for estimating the possible fruit yield. They designed an image processing technique including image segmentation with R/B value combined with V value and a circle fitting using curvature analysis. An individual tree yield estimation model on an ANN (Artificial Neural Network) was developed. The system was used for an experimental Fuji apple orchard. They selected twenty-six tree samples from a total of 80 trees whereas 21 groups of data were trained and 5 groups of data were validated. They calculated that the average actual training dataset was 40.36 kg and the validation dataset was 40.52 kg. They used a back propagation neural model to develop a prediction model for fruit yield estimation.

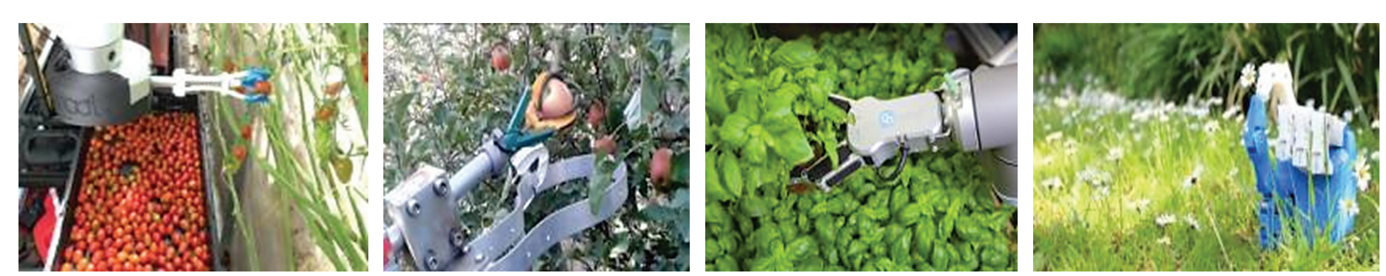
Fu et al. (2018) proposed a new method to estimate the yield of kiwifruit orchard using image processing techniques with an android mobile phone. They selected significant color channels and their threshold for image segmentation. Then they generated a binary image, and the noise from the images was removed. They also developed a fruit-counting algorithm to evaluate the number of kiwifruits by identifying the number of fruit calyxes. This algorithm was validated for 100 kiwifruit images. They achieved a good precision and recognition ratio of 76.4% with this proposed method. The outcome of their research specified that a yield estimation method for kiwi fruit orchards would be valuable for yield forecasting and harvest schedule planning.

Digital Image processing application for robot harvesting

Oktarina et al. (2020) did their research work to discuss a pilot project of employing a robot as a harvesting robot. The objective of this study was to establish the initial project in generating a series of robots applied in agriculture to realize the idea of digital farming. The novelty of their study was that this method is simple, and image processing is kept simple to accommodate processors' restricted computation resources. The robot design was customized according to the size of the tomato tree and tomato. The tomato location was indicated by a circle resulting from the image processing and divided into left, right, and middle positions in the image plane. The arm robot moves to the left and harvests the tomato. The average time for harvesting both red and green tomatoes was 4.932 s, and 5.276 s, respectively. The required time for the robot to detect a red tomato and return to a standby position was 9.676 s, and 10.586 s for the green tomatoes. This time the difference was due to the robot's distance to the tomato and not the color of the tomato. The experiment showed that the robot successfully harvested the tomatoes at the site specified in their study, and proved the effectiveness of this robot design as an agriculture robot.

Zhang et al. (2021) developed a justifiable robotic system for apple harvesting with prototype. They developed a system for fruit detection and localization using deep-learning algorithm and vacuum-based end-effector for apple detachment. Moreover, a nonlinear control structure was developed to accomplish accurate and responsive motion control. They conducted field experiments also to demonstrate the performance of the established apple harvesting robot.

Kumar et al. (2019) developed an autonomous system for flower harvesting. They applied a watershed algorithm to detect the flowers and a robotic arm is used to cut the flower stems when the signal is received to it via a microcontroller. The different kinds of robot harvesting are illustrated in Figure 11.



(a) (b) (c) (d)

Figure 11. (a) Vegetable picking robot (b) Fruit picking robot (c) herbs picking robot (d) Flower picking robot

Tabular representation of numerous image processing methods in agriculture

Table 1. List of studies focused on different types of image segmentation techniques

Authors, year	Methods	Description	Advantage	Disadvantage
Xiao et al. (2020)	Otsu's method	Most successful method for image thresholding and simple calculation. It is a widely used method which considers pixel gray information only.	Provides good segmentation result.	Ignores spatial correlation and its anti-noise capability is poor.
Jayanthi and Shashikumar (2017)	K-means clustering	Images are segmented into the same cluster based on the features of image	Works faster for the smaller value of K.	Difficult to predict K value. With global cluster it did not work well.
Hetal J. Vala and Astha Baxi (2013)	Watershed segmentation	Morphological gradient based image segmentation	Provides very good segmentation result and meets criteria of less computational complexity.	It is highly sensitive to local minima and for noisy image it influences the segmentation.
Alden et al. (2019)	Artificial Neural Network (ANN)	Represents a set of algorithm which is used in prediction of variables beyond the dataset.	Well suited to analyze complex numbers and dynamic ANN is suitable for exploration task.	Requires more processing time and large training samples.

Table 2. List of studies focused on color image enhancement techniques

Authors, year	Enhancement methods	Description	Advantage	Disadvantage
Aarthy and Sumathy (2014)	Histogram equalization	Graphical distribution of pixels of image data	Increases the contrast of the image.	This method will be a failure if the gray values are far apart of the image.
Fan et al. (2020)	Homomorphic Filtering	Improves the contrast of the image and compresses it in the dynamic range.	Removes the multiplicative noise of the image	Problem of image bleaching
Vishwakarma and Mishra (2012)	Retinex	Advance technique for color image enhancement	Makes available dynamic range compression	Gray level violation problem and unnatural color rendering

Table 3. List of studies focused on advanced feature extraction techniques

Authors, Year	Methods	Description	Advantage	Disadvantage
Humeau-Heurtier (2019)	GLCM/SDLCM approach	Studies the gray level distribution of a pair of pixels	Easy to implement and shows very good result	High dimensionality of the matrix
Humeau-Heurtier (2019)	Gabor decomposition	Excellent tool for image segmentation and boundary detection	Computational efficiency and stoutness	Computationally expensive
Shrestha and Mahmood (2019)	Deep learning method	Convolution neural network used in computer vision	Learning the high level features from raw data automatically	Higher computational complexity and is expensive

Conclusion

Digital image processing and machine learning have made significant breakthroughs in the agriculture sector. Yield quality, weed detection, plant disease, use of pesticides, and irrigation monitoring are the key concerns in agriculture. Recent advancements in different types of machine learning image processing techniques are used for accurate classification and decision-making in crop management, irrigation, yield mapping, fruit grading, and so on. A neural network can be a cost-effective tool for the usual classification of plant leaf diseases, as a machine learning classifier is used to detect weeds and robots with a machine vision system to harvest fruits and vegetables. As fields and farms grow day by day, better monitoring systems are essential for automated management and reduced expenses, from which farmers could benefit more. However, it could be possible to integrate image processing with the techniques of the internet of things (IoT), big data applications, as well as other emerging technologies, which could enable farmers to achieve satisfactory results more efficiently without the need for constant physical field assessments. The success of translating farmers' field knowledge into AI training programs will depend on increased technical and educational investments in the agricultural sector. The application of digital image processing and machine learning in agriculture is an important catalyst that has the potential to revolutionize farming techniques and contribute to global food security in an era of increasing population and sustainability concerns. Future research should focus on overcoming the aforementioned issues and developing novel approaches to making these technologies more available to a broader range of farmers, ensuring that the benefits are wide-ranging and comprehensive.

Acknowledgement

There was no research grant or external funding. We must give thanks to faculty members of Bangnabandhu Sheikh Mujibur Rahman Agricultural University for proper guidance and inspiration.

References

Aarthy M and Sumathy P, 2014. A comparison of histogram equalization method and histogram expansion. International Journal of Computer Science and Mobile Applications, 2, 25-34.

Aggelopoulou AD, Bochtis D, Fountas S, Swain KC, Gemtos TA and Nanos GD, 2010. Yield prediction in apple orchards based on image processing. Springer Science+Business Media, LLC 2010.

Alden KM, Omid M, Rajabipour A, Tajeddin B and Firouz MS, 2019. Quality and shelf-life prediction of cauliflower under modified atmosphere packaging by using artificial neural networks and image processing. Computers and Electronics in Agriculture, 163, 104861.

Al-Hiary H, Bani-Ahmad S, Reyalat M, Braik M and AL Rahamneh Z, 2011. Fast and accurate detection and classification of plant diseases. International Journal of Computer Applications, 17, 0975-8887.

Bargava A and Bansal A, 2021. Fruits and vegetables quality evaluation using computer vision: A review. Journal of King Saud University - Computer and Information Sciences, 33, 243-257.

Bavithra K and Lavanya AP, 2019. Weedicide spray robot using image processing. International Research Journal of Engineering and Technology (IRJET), e-ISSN: 2395-0056 6, 06.

Cubero S, Alegre S, Aleixos N and Blasco J, 2015. Computer vision system for individual fruit inspection during harvesting on mobile platforms. Precision agriculture, 15, 547-552.

Fan Y, Zhang L, Guo H, Hao H and Qian K, 2020. Image processing for laser imaging using adaptive homomorphic filtering and total variation. In Photonics, 7, 30. https://doi.org/10.3390/photonics7020030

Calafell Font D, 2014. Application of image processing methodologies for fruit detection and analysis. Engineering and Information Technologies, University of Lleida, July, 2014.

Fu L, Liu Z, Majeed Y and Cui Y, 2018. Kiwifruit yield estimation using image processing by android mobile phone. Elsevier, IFAC-PapersOnLine, 51, 185-190.

Ganatra N and Palet A, 2018. A Survey on disease detection and classification of agricultural products using image processing and machine learning . International Journal of Computer Applications, 180, 0975-8887.

Hetal JV and Baxi A, 2013. A Review on Otsu Image Segmentation Algorithm, International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2, 2, https://doi.org/10.48550/arXiv.2106.10698

Humeau-H A, 2019. Texture feature extraction methods: A survey. IEEE Access, 7, 8975-9000.

International Journal of Computer Science and Mobile Applications, 2, 25-34.

Jayanthi MG and Shashikumar DR, 2017. Survey on agriculture image segmentation techniques. Asian Journal of Applied Science and Technology (AJAST), 1, 143-146.

Kothawale SS, Barbade SR and Mirajkar PP, 2018. Grape leaf disease detection using SVM classifier. International Journal of Innovative Research in Computer and Communication Engineering, 6, 4.

Kulkarni P, Karwande A, Kolhe T, Kamble S, Joshi A and Wyawahare M, 2021. Plant disease detection using image processing and machine learning. ArXiv preprint arXiv:2106.10698.

Kumar AV, Kannarasu V, Padmapriya S, Partheeban N and Arun S, 2019. Design and implementation of autonomous flower harvester using image processing. International Journal of Recent Technology and Engineering (IJRTE), 8, 2638-2642.

Melesse TY, Bollo M, Pasquale D, Centro VF and Riemma S, 2022. Machine learning-based digital twin for monitoring fruit quality evolution. Procedia Computer Science, 200, 13-20.

Narendra VG and Hareesh KS, 2011. Study and comparison of various image edge detection techniques used in quality inspection and evaluation of agricultural and food products by computer vision, International Journal of Agricultural and Biological Engineering, 4, 83-89.

Narendra VG and Hareesha KS, 2010. Prospects of computer vision automated grading and sorting systems in agricultural and food products for quality evaluation. International Journal of Computer Applications, 1, 0975-8887.

Oktarina Y, Dewi T, Risma P and Nawawi M, 2020. Tomato harvesting arm robot manipulator, a pilot project. In Journal of Physics: Conference Series, 1500, 012003, IOP Publishing.

Otsu N, 1979. A Threshold Selection Method from GrayLevel Histograms. IEEE Transactions on Systems, Man, and Cybernetics, 9, 62-66.

Patil JK and Kumar R, 2011. Advances of image processing for detection of plant diseases. Journal of Advanced Bioinformatics Applications and Research, 2, 135-141.

Prabha DS and Kumar JS, 2014. Image processing methods and its role in agricultural sector- A study. International Journal of Business Intelligents, ISSN: 2278-2400, 3, 366-373.

Qian J, Xing B, Wu X, Chen M and Wang Y, 2018. A smartphone based apple yield estimation using image features and ANN method in mature period. Scientia Agricola. DOI: http://dx.doi.org/10.1590/1678-992X-2016-0152

Rupali SJ and Patil SS, 2013. A fruit quality management system based on image processing. IOSR Journal of Electronics and Communication Engineering (IOSR-JECE), 8, 01-05. DOI:10.9790/2834-0860105

Sandeep KK, Rajeswari and Usha BN, 2018. Convolutional neural network based weed detection in horticulture plantation. International Journal of Scientific Research and Review, 7, 6, ISSN 2279-543X.

Sarmad H and Imran A, 2018. Detection of weed and wheat using image processing. Proceedings , from the IEEE 5th International Conference on Engineering Technologies & Applied Sciences, 22- 23 Nov, 2018, Bangkok, Thailand.

Schwalbert RA, Amado T, Corassa G, Pott LP, Prasad PV and Ciampitti IA, 2020. Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil. Agricultural and Forest Meteorology, 284, 107886.

Shrestha A and Mahmood A, 2019. Review of Deep Learning Algorithms and Architectures. Digital Object Identifier 10.1109/ACCESS.2019.2912200.

Singh V and Misra AK, 2017. Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture, 4, 41-49.

Sun G, Jia X and Geng T, 2018. Plant disease recognition based on image processing technology. Journal of electrical and computer engineering, Article ID 6070129, 7 pages.

Vibhute A and Bodhe SK, 2012. Applications of image processing in agriculture: A survey. International Journal of Computer Applications, 52, 0975-8887.

Vishwakarma AK and Mishra A, 2012. Color image enhancement techniques: a critical review. Indian Journal of Computer Science and Engineering, 3, 39-45.

Xiao L, Ouyang H, Fan C, Umer T, Poonia RC and Wan S, 2020. Gesture image segmentation with Otsu's method based on noise adaptive angle threshold. Multimedia Tools and Applications, 79, 35619-35640.

Zhang K, Lammers K, Chu P, Li Z and Lu R, 2021. System design and control of an apple harvesting robot. Mechatronics, 79, 102644.

AGRICULTURAL SCIENCE AND TECHNOLOGY, VOL. 15, No 4, pp 23-27, 2023
Published by Faculty of Agriculture, Trakia University, Bulgaria
ISSN 1313-8820 (print)
ISSN 1314-412X (online)
http://www.agriscitech.eu
DOI: 10.15547/ast.2023.04.034

Genetics and Breeding

Growth, survival rate of New Zealand White, Dutch Rabbit and their crosses

U.A. Eshimutu[1]*, U.A. Umar[2], A.K. Olutunmogun[2], A.C. Oladimeji[1], M. Aliyu[1], A.K. Okpanachi[1]

[1]Animal Genetics and Breeding Department of Animal Health and Production Technology Federal College of Agriculture, Akure Ondo State, Nigeria
[2]National Animal Production Research Institute, Ahmadu Bello University, Zaria, Kaduna State, Nigeria

(Manuscript received 19 June 2023; accepted for publication 14 November 2023)

Abstract. *The aim of the study was to assess survival rate of crossbred New Zealand White and Dutch rabbit breed. A total of 16 mature rabbits of seven to nine months old, New Zealand White and Dutch were used for the study. Data obtained were subjected to analysis of variance ANOVA using SAS. The reproductive traits studied were litter size, litter birth weight, mean kit weight. The growth traits were: body weight, body length, ear length, chest circumference, hind limbs, thigh length, nose to shoulder and thigh circumference. The reproductive traits were significantly ($P<0.05$) affected by genetic group Pure and crosses. New Zealand White observed high litter size and litter birth weight at first, seventh, 14th and 21st day. Purebred Dutch had significant ($P<0.05$) high values for growth traits. The body weight 478.73±18.10, body length 33.12±0.42, ear length 9.10±0.09, chest circumference 18.24±0.45 and hind limbs 19.51±0.33 were significantly ($P<0.05$) high in crosses of Dutch x New Zealand White. Pre-weaning mortality and survival rate at weaning were 22.22% and 77.77% high in New Zealand White; 14.28% and 85.71% in Dutch and DUC x NZW; and 9.09% and 90.90% in NZW x DUC. In conclusion, New Zealand White x Dutch crosses demonstrated high survival rate and low pre-weaning mortality.*

Keywords: breed, crossbreed, litter trait, pre-weaning, mortality

Introduction

Protein deficiency can be alleviated through animal production and rabbit has immense potentials such as short gestation period and high nutritional quality meat (Ajala and Balogun, 2004). The rabbit possesses good characteristics, thus, are as follows; high growth rate, high prolificacy relatively low cost of production, sodium and cholesterol (Esfandyari et al., 2015). Consumption of protein especially from animal source such as ruminants e.g. sheep, goat, cattle and monogastric animals poultry and swine are insufficient (Owen et al., 2008). However, it is important to look into other alternative source of bridging the gap of protein deficiency in Nigeria (Owen et al., 2008). Less consumption of protein from animal source has for long afflicted many developing countries such as Nigeria (Owen et al., 2008). Human population growth in developed countries is stabilizing whereas that of developing countries, Nigeria inclusive, is still increasing rapidly. However, searching for alternative sources of protein to meet up the population challenge is imperative (Owen et al., 2008). Crossing does not only take advantage of traits with considerable non-additive genetic variation but also exploits differences between populations as a deviation from overall mean between populations (Ahmed, 2003). Crossing of rabbits which are micro-livestock plays a significant role in overcoming low protein consumption in Nigeria (Oloruntola et al., 2015). The breeder uses crossbreeding as the fast and easier way of improving body weight and morphological traits in rabbit due to hybrid vigor and complementary effect (Esfandyari et al., 2015). The quality of largescale rabbit production in commercialized way mostly lined on the litter traits such as litter size at birth and the survivability of the

*e-mail: uabdullahi1982@gmail.com