Environment Conservation Journal, 22 (SE):55-62, 2021
ISSN 0972-3099 (Print) 2278-5124 (Online)
DOI: https://doi.org/10.36953/ECJ.2021.SE.2206
https://www.environcj.in/

Advancements in farming and related activities with the help of artificial intelligence: a review

Sidhu, K. S., [1]✉ **Gill, A.S.,** [1] **Arora, A.,** [1] **Singh, R.,** [2] **Singh, G.,** [1] **Verma, M. K.,** [1] **Kaur, B.** [3]

Received: 06.11.2020 **Revised: 12.01.2021** **Accepted: 20.01.2021**

Abstract

The demands of population are gradually increasing rapidly. Most manufacturing and processing industries face obstacles or problems to fulfil this daily increase in demand. Even if the demand can be managed, the transmission of diseases through these sectors is also a considerable concern. Many new technologies are being used to avoid unbearable consequences, which arise because of human-to-human contact or interaction. Higher firms adopt a ton of computer software and other modern technologies to get rid of such problems. Farming, one among the essential professions is also being impacted; however, human beings have come a long way since they started farming. This paper examines how one of the latest technologies, Artificial Intelligence, has helped improve farming, agriculture, and related tasks to increase yield and productivity. How Animal Farming, Detection of Diseases in Plants, Grading processes of Agricultural Foods, and quality check of vegetables and fruits, have advanced with the aid of Artificial Intelligence, is summed up in the subsequent sections.

Key Words: ***Agriculture***, ***artificial intelligence***, ***computer vision***, ***farming***, ***diseases***, ***machine learning***

Introduction

Diseases spreading by viruses, bacteria, fungi, and other micro-organisms are becoming a huge concern and challenge for humankind. Most of the infections spread by physical contact. COVID-19, a viral infection that has become a big challenge for the world has also caused an enormous disturbance in food processing industries where human contact is unavoidable (Sain et al., 2020). This, in turn, is not only impacting financial aspects but also man, material and environmental factors. With Artificial Intelligence's help, one can solve such problems of human contact and uplift humankind's safety factor by complementing manual labour with new-age technology and computer software (Marinoudi et al., 2019; Singh et al., 2020). The factor of hygiene can also be improved by replacing manual labour with the help of machines/equipment using Artificial Techniques and principles in different sectors and industries like production, packaging, printing, etc. As a result, the production or yield will increase as well as the time of processing and cost of production per piece will reduce. Occupational injuries and human errors are also a big concern in these sectors. Since programming works by using predefined operators and functions and the computer is capable of doing the same work tirelessly, infinitely and more accurately, all these problems are being tackled effectively with Artificial Intelligence techniques which are also playing a profound and scientific role for the upliftment and betterment of the society (Blackwell, 2002).Being one of the most important professions, farming also forms an essential aspect of sustenance for the entire population. The introduction of new technologies and better techniques has changed farming and its yield, improving it substantially. With an increasing population and the agricultural land becoming even scarcer, humans have to be more innovative than before to produce maximum yield. Artificial Intelligence; the intelligence demonstrated or displayed by machines, has solved many problems and has helped make the efficient utilisation of the limited resources available. It has helped to advance and develop numerous industries and fields, including agriculture and farming. Machine Learning is one of the Artificial Intelligence

Author's Address
[1]Department of Computer Science and Engineering
[2]Department of Mechanical Engineering
[3]Department of Agricultural Engineering
Baba Banda Singh Bahadur Engineering, Punjab, India
E-mail.: ***karamveersidhu14@gmail.com***

applications that equip machines with the capability to learn naturally and improve from experience without the requirement to program them explicitly (Michalski et al., 1983). Below are a few uses of artificial intelligence (AI) in agriculture/farming:

•Fruit picking in quicker time with least human resources.

•Crop/yield analysis in an efficient manner in lesser time.

•Identifying and eradicating weeds in an efficient manner, with least wastage and safe manner.

•Soil Sample analysis report will help identify the type of defects in soil and select the type of fertiliser.

•Real-time weather condition data capture and forecast, especially relative humidity, temperature, rain, and solar radiation. When combined with the AI, the data will be able to prevent crop losses and /or increase yield.

•Technology can be used in creating a smart livestock monitoring system and thus help in productivity increase.

Machine learning (ml) in animal farming

To better understand the well-being of livestock, ML is penetrating farming. Dutta et al. (2015) have presented an ML model that classifies animal behaviour based on collar sensors' data. Many unsupervised and supervised ML models have been discussed, but the most accurate is the bagging ensemble classification with Tree learner. The model's accuracy was 96%. Behaviour like resting, grazing, walking, ruminating were tracked for classification. The study showed that supervised machine learning technology could be inducted for accurate classification of cattle and provides immense potential in gauging animal health problems such as lameness. Pegorini et al. (2015) have presented a system that classifies chewing patterns of grazing animals. Ingestive behaviour in animals that graze is of extreme importance for better growth and improved health. In the study, food intake patterns were considered. The biomechanical strain occurring during jaw movements was measured using data collected with optical fibre Bragg grating sensors (FBG). The developed model's classification accuracy is 94%. Matthews et al. (2017) have discussed a monitoring system which is automated using ML. The system tracks the pig movements using depth video cameras. The cameras monitor activities like standing, moving, drinking and feeding. This method has the potential of changing how livestock breeders look after their livestock. Craninx et al. (2008) has described a machine learning technique that predicts the rumen fermentation pattern from milk fatty acids. Morales et al. (2016) used Support Vector Machines (SVM) to detect problems early in commercial eggs production. The technique achieved an accuracy of 0.9854. The egg production data from a farm were utilised for the study. Alonso et al. (2015) also show the use of SVM to foresee the weight of livestock animals. Bovines of different ages and breeds were used to collect data. Livestock breeders should have the tools to foresee the weight of their livestock accurately. A model that predicts the weight of carcass is presented by Alonso et al. (2013). The study was done on the beef breed.

The carcass weights can be predicted 4-5 months before the slaughter day using the developed model. The authors used SVM for regression for developing the model. Hansen et al. (2018) aim to tackle the problems with the current method of radio frequency identification (RIFD) tags for identification of animals, which is time-consuming and uncomfortable for the animals. A convolution neural network (CNN) model was trained using digital images for pig face recognition.

Techniques using artificial intelligence to detect plant diseases

DCNN (Deep convolutional neural networks), also called ConvNet, belongs to the deep neural network category, which is generally used as a visual imagery technique. It is currently most prevalent in detecting plant disease as it helps in tracking plant-related pest diseases with great efficiency. The technique is more preferable as it's not labour intensive so it could be a practical approach for computational analysis of plant disease. Recently, a study reported Artificial Intelligence-based DCNN and transfer learning system to provide accurate predictions for diseases and pest detection in banana (Selvaraj et al., 2019). Convolutional neural network model named LeNet detects and identify diseases in tomato leaves (T m et al., 2018). Apple leaf diseases were identified based on Deep

Convolutional Neural Networks using AlexNet architecture (Liu et al., 2018). 3D CNN model is used for charcoal rot disease as it can automatically learn Spatio-temporal features without handcrafting, with high accuracy (Nagasubramanian et al., 2019). Hyperspectral imaging is a preferable technique to identify various crop diseases as it is non-invasive and a fast detection method. Under this push, broom technology and snapshot technology are the recent ones helping in the proper analysis of crop condition. Hyperspectral imaging as well as machine learning techniques both help to differentiate between healthy capsicum plants and those infected by Tomato Spotted Wilt Virus (TSWV) (Moghadam et al., 2017) and also help to detect the Tobacco Mosaic Virus (TMV) disease in very less time (Zhu et al., 2017). Three Dimensional Hyperspectral plant models had been studied to detect Cercospora leaf spot disease in sugar beet leaves (Roscher et al., 2016). Hyperspectral reflection and transmission measurements were conducted to study Blumeria graminis f. sp hordei infection in barley (Thomas et al., 2017). Artificial Intelligence-based thermal and stereo image technology supports the classification of powdery mildew disease of tomato (Prince et al., 2015). Mokhtar et al. (2015) reported a tomato yellow leaf curl virus classification using supervised machine learning support vector machine models pipeline (Mokhtar et al., 2015). The problem of pest diseases can be tackled with an innovative app launched, named Plantix app (Plant doctor) in which the photo of the infected plant is captured, analysed, compared with prior information and then at last treatment options as well as preventive measures are provided to maintain the health of the plant (Tibbets and John., 2018). Similarly, the newest Artificial Intelligence based algorithms for Cloud-based image processing has allowed real-time diagnosis and help the experts to analyse the extent of disease with geographical visualisation (Singh, 2018). The innovation of artificial intelligence nose (electronic nose) is considered a fast and non-invasive technique for detecting plant diseases (Cui et al., 2018). To assess and monitor plant stresses such as pests, diseases, drought, and weeds, unmanned aerial vehicles (UAVs) and drones, are used (Barbedo et al., 2019). UAVs and deep CNN are used to capture high-resolution images of infected plants so that the plant-associated diseases such as a foliar disease in maize caused by Setosphaeria turcica, in the case of Northern leaf blight (NLB) (Wu et al., 2019) and soybean leaf diseases (Tetila et al., 2019) can be easily detected. Spatial and spectral data have been developed on hyperspectral UAV images, using a deep learning model called the multiple inception-racenet models to detect yellow corrosion in wheat (Saleem et al., 2019). Table 1 shows a comparison of various deep learning approaches in terms of different performance metrics. Five kinds of diseases in apple plant were classified and detected with the help of a state-of-the-art CNN model, i.e. VGG-inception architecture was successful in detecting apple diseases and also outclasses the activity of other DL architectures like AlexNet, GoogLeNet, several versions of ResNet, and VGG for clarity of diseases in the plants (Jiang et al., 2019). Modern deep learning model helped detect pest infecting rice plants using novel Artificial Intelligence and IoT (Internet of things) methods (Win et al., 2018). Artificial Neural network and diverse image processing techniques are used for the detection of cotton leaf diseases (Ranjan et al., 2015). A Robust Deep-Learning-based detector has been developed to monitor diseases and recognise pests in Tomato Plants' real-time (Fuentes et al., 2017). CNN's Transfer learning is used for identifying plant leaf's diseases using VGGNet already pre-trained on the ImageNet database and Inception module (Chen et al., 2020). This approach is used to recognise the image of cassava disease infected plants and is a fast and affordable strategy for detecting diseases in plants digitally (Ramcharan et al., 2017). To detect diseases subsisting in leaves automatically, Neural Networks are being used. This approach provides accurate detection in leaf and is an important method, in the case of the stem, and root diseases with fewer computation efforts and is also moreover, less labour intensive.

Grading process for agricultural foods using artificial intelligence

In the present era of advanced technologies, both the hardware and software features reduce human efforts and yield better results. The use of AI in the agriculture sector has become a trend among various developed countries. In today's industrial world, the consumer demands products of good quality. The machine vision technique of grading system has been developed to conquer these problems and lessen labour requirements. For a machine vision system, the hardware, as well as the software, is required.

Table 1. Comparison of several Deep Learning approaches in terms of various p erformance metrics (retrieved from Saleem *et al.*, 2019)

DL Architectures/Algorithms	Datasets	Selected Plant/s	Performance Metrics (and Their Results)
CNN	PlantVillage	Maize	CA (92.85%)
AlexNet, GoogLeNet, ResNet	PlantVillage	Tomato	CA by ResNet which gave the best value (97.28%)
LeNet	PlantVillage	Banana	CA (98.61%), F1 (98.64%)
AlexNet, ALexNetOWTBn, GoogLeNet, Overfeat, VGG	PlantVillage and in-field images	Apple, blueberry, banana, cabbage, cassava, cantaloupe, celery, cherry, cucumber, corn, eggplant, gourd, grape, orange, onion	Success rate of VGG (99.53%) which is the best among all
AlexNet, VGG16, VGG 19, SqueezeNet, GoogLeNet, Inceptionv3, InceptionResNetv2, ResNet50, Resnet101	Real field dataset	Apricot, Walnut, Peach, Cherry	F1(97.14), Accuracy (97.86 ± 1.56) of ResNet
Inceptionv3	Experimental field dataset	Cassava	CA (93%)
CNN	Images taken from the research center	Cucumber	CA (82.3%)
Super-Resolution Convolutional Neural Network (SCRNN)	PlantVillage	Tomato	Accuracy (~90%)
CaffeNet	Downloaded from the internet	Pear, cherry, peach, apple, grapevine	Precision (96.3%)
AlexNet and GoogLeNet	PlantVillage	Apple, blueberry, bell pepper, cherry, corn, peach, grape, raspberry, potato, squash, soybean, strawberry, tomato	CA (99.35%) of GoogLeNet
AlexNet, GoogLeNet, VGG- 16, ResNet-50,101, ResNetXt-101, Faster RCNN, SSD, R-FCN, ZFNet	Image taken in real fields	Tomato	Precision (85.98%) of ResNet-50 with Region based Fully Convolutional Network(R-FCN)
CNN	Bisque platform of Cy Verse	Maize	Accuracy (96.7%)
DCNN	Images were taken in real field	Rice	Accuracy (95.48%)
AlexNet, GoogLeNet	PlantVillage	Tomato	Accuracy (0.9918 ± 0.169) of GoogLeNet

To capture the images of products, hardware like the camera and computer is required. Then features of the respective images are collected through a computer, and each and every feature is analysed, using Image processing techniques (Elakkiya et al., 2018). Artificial Intelligence has become prominent and budding technique, even used for consumers feedback (Tsoumakas, 2018). When a consumer seeks some changes in a product, he can provide feedback, and the machines can automatically yield those desired results. Therefore, the product's quality is easily determined, and it also leads to a reduction in time. Also, the new process of "Grading System" seems to be as of good interest for farmers. The Grading system helps to draw outcomes from various surveys and instruct machines according to it. It also helps the producer to track the status of the product until it gets to the customer. All this reduces human efforts and saves precious time. Many users have confirmed that AI has provided better results with errors approaching zero. Artificial Intelligence techniques have also been used to improve the grading system, to get a precise value. The grading system's AI techniques are used to well develop the food industry's industrial products, for instance, the agricultural products. However, the Grading system varies for each product or item as required by either owner or customer(Nychas et al., 2016). The other form of survey is used for segregation of the good quality products from the bad quality products. This feature has emerged out as a boon for the agricultural society. Nowadays, the researchers are working to advance the existing technology by minimising the error in this technique's output. A comparative analysis of fruit grading is shown in Table 2.

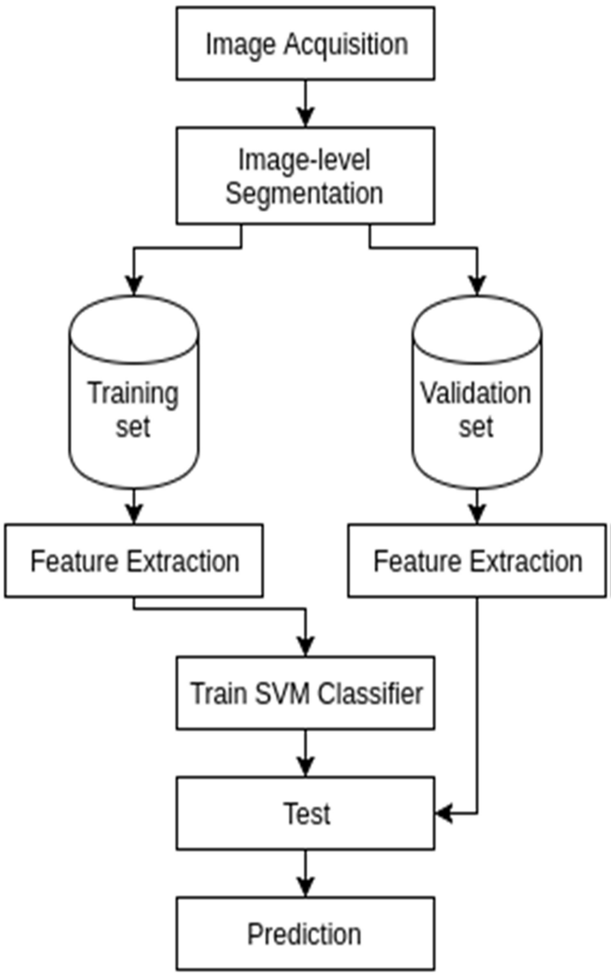
Table 2. Comparative analysis of fruit grading (retrieved from Elakkiya *et al.*, 2018)

Fruits	Features	Technique	Accuracy
Mango	Colour of the image changes.	IR vision sensor and Gaussian Mixture Model.	Not specified
Harumani Mangoes	Shape, colour, weight of the mangoes.	Fourier Based separation model.	90%
Cashew	Colour, texture, size and shape of cashews.	Multi resolutional Wavelet transform and AI (classifier) of SVM and BPNN	95%
Cherry Tomato	Colour, texture, shape (external and internal) characteristics	AI technique of SVM and KNN classifier.	Not specified
Peanut	Shape, texture and colour of peanuts.	AI technique of BPNN.	Not specified
Apple	Skin or surface of the apple and colour.	AI technique of FNN and SVM.	89%

Artificial intelligence to check the quality of vegetables and fruits

Automatic identification of vegetables and fruits is achieved with computer vision along with machine learning. Block diagram attributed to the classification process is manifested in figure 1 (Jana et al., 2017). Automatic harvesting is a growing field that collects useful information about growing, cultivating, checking the ripeness of vegetables and fruits, along with other aspects of farming with the help of computer vision and machine intelligence. Fruit picking and sorting are also taking place these days with the help of computer vision. In most farm industries, ripeness is still checked manually by humans but assessing the ripeness level precisely is different even for expert inspectors. In one of Amazon's tests, the evaluators reached dissimilar results in twenty per cent of the tests, despite examining the quality of the same vegetables and fruits. In the automatic ripeness detection system, vegetables and fruits are transported in containers to a special sensor with the help of a conveyor belt. The sensor appears like a typical camera, but it can gather the imperceptible information to the human eye. Using machine learning's principles, the machine learns about good and bad products with the help of the input provided. New product versions are provided as daily input. Images of the products are captured and then given as data to the machine. It allows the computer to understand the quality of vegetables and fruits.Fruits are split up into different classes: "OK", "Damaged", "Severely Damaged" and "Expired". Cases containing vegetables and fruits of different ripening categories are introduced regularly into the machine. Similarly, employees know only through the screen of how the entire container will be filled. This helps prevent every third case being packed with "damaged" fruits and vegetables or every fourth case with "healthy" fruits. Instead of permitting the machine to grasp the sequence without proper product testing, it actually prevents the machine from grasping a pattern.

Figure 1. Block diagram of a classification process (retrieved from Jana *et al.*, 2017)



Conclusion

Artificial Intelligence, one among the modern technologies and a broad field, has a ton of applications. It is extensively used in farming, agriculture and related activities, and aims to achieve more effective and efficient results that otherwise were not possible by following the traditional practices. It is evolving day by day, and scientists are trying to find even better solutions to solve the modern-day problems more optimally and sustainable development.

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