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## Review Paper

### Role of artificial intelligence in achieving global food security: a promising technology for future

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**Abstract:** Rapid growth of population, diminishing natural resources, climate change, shrinking agricultural lands and unstable markets are making the global food systems rather insecure. Therefore, modern agriculture and food systems should be more productive in terms of output, efficient in operation, resilient to climate change and sustainable for the future generations. As a result, the need of a

technological transformation is greater than ever before. Being a recent advancement in computer sciences, Artificial Intelligence (AI) has the capacity to address the challenges of this new paradigm. Hence, understanding the importance and applicability of AI in agriculture and food sector could be vital in the journey towards achieving global food security. This review focuses on the AI applications in relation to four pillars of food security (food availability, food accessibility, food utilization and stability) as defined by FAO, in detail. The AI technologies are being applied worldwide in all four pillars of food security even though it has been one of the slower adopted technologies compared to the rest. Nevertheless, it warrants exploring the capabilities of AI and their current impact on the food systems. It is eminent that AI technology has a key role to play in the future agriculture sector. The worldwide AI in agriculture market is expected to reach USD 2,075 million by 2024. Present article reveals how AI technologies could benefit global agriculture and food sector, and examines the ways by which AI can address the prominent issues in Sri Lankan agriculture sector such as labor scarcity, misuse of agrochemicals and inefficient food value chains. Though there are still many challenges and gaps to be addressed at research, policy, administrative and farmer levels, the immense potential of this novel technology should be exploited fast in the journey towards global food security.

**Keywords:** Artificial intelligence, agriculture, food security, precision farming, livestock



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## Introduction

Achieving the goal of ending global hunger, aligning with the United National Sustainable Development Goals (SDG) – 2, often means providing food for the people in need (Jorgensen and Costanza, 2016). The FAO (2008) has defined food security as “all people at all times, have physical and economic

access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life”. Nearly 690 million people are hungry worldwide and it is increased up by nearly 60 million in five years (FAO, 2020)

among which majority of undernourished people live in developing countries (Porter *et al.*, 2012).

Food security and food insecurity are multi-dimensional phenomena, which several indices involve to measure hunger (Clay, 2002). The Food Insecurity Multi-Dimensional Index (FIMI) creates four dimension/pillars of food security, namely, availability, access, utilization and stability of food, and they all need to be addressed comprehensively though a coherent approach in achieving global food security (FAO, 2008).

The first necessary dimension in order to achieve food security is availability, which indicates the presence of food in a country through all forms of domestic production, food stocks, imports and food aid (Riely *et al.*, 1999). The food access is the “physical, economic and social possibility to a person to access the food” (Shaw, 2007), and consists of three elements, namely, physical, financial and socio-cultural. The physical element gives the picture about unavailability or inefficient transport facilities to food deliveries across the country. The economic element illustrates the situation of people according to their affordability to buy sufficient food (Napoli *et al.*, 2011). The socio-cultural element explains that food is physically available and people have the ability to purchase food but it is disturbed from the gender or being a member of the particular social group (Riely *et al.*, 1999). The availability and access to food alone is not adequate, as people need to have a “safe and nutritious food”. Sufficient energy should be there in order to engage the daily physical activities after consumption of foods. Adequate sanitary facilities to avoid the spread of diseases, safe drinking water and the awareness of food preparation and food storage also included. Utilization, which the third dimension, therefore, covers the diverse aspects by combining consumers' understanding on which food to select, how to prepare it and store them (Napoli *et al.*, 2011). Food stability must be present at all times to exist the availability, access and utilization of the food security. This fourth dimension highlights the importance to reduce the possibility of adverse effects on the other three dimensions. Adverse weather conditions, political instability, strength of legal rights, may impact on the individual food security status (Napoli *et al.*, 2011)

Global demand for food is growing continuously as a result of population growth, threatening to the

global sustainability issues, including food security. World population will continue to increase up to 9.7 billion in 2050 (Gerland *et al.*, 2014). Meanwhile people are searching for basic needs for their compatible life with higher purchasing power, which always raise the demand for food (Lewis and Nocera, 2006; Chen *et al.*, 2016) and increase the pressure on food production systems, lands, and energy (Chamara and Beneragama, 2020). As it stands, emerging technologies of the Fourth Industrial Revolution (4IR) including Artificial Intelligence (AI) have the potential to overcome the structural weaknesses of the current food systems and deliver more productive, competitive and sustainable outcomes (Liao *et al.*, 2018)

Use of AI in the agricultural and food production context has gained prominence, in the beginning of 2015 (Lakshmi and Corbett, 2020) and is still in its early stages. The AI technologies have been actively embraced in North America and Europe. There are increasing efforts have been developing in Africa and Asia particularly Japan, India and China. The worldwide AI in agriculture market was valued at around USD 545 million in 2017 and is expected to reach approximately USD 2,075 million by 2024, at a Compound Annual Growth Rate (CAGR) of slightly above 21% between 2018 and 2024 (Globenewswire, 2020). However, there is a huge potential to develop this technology in order to address critical issues related to food security while respecting and addressing the environmental concerns.

Artificial intelligence refers to the simulation of human intelligence through machines that are programed to think like humans and mimic their actions (Russell and Norvig, 2016) from the simplest to more complex tasks. The goals of AI include learning, reasoning, and perception (Copeland and Proudfoot, 2004). The term may also be applied to any machines that exhibit characters associated with a human mind such as learning and problem solving, ability to rationalize and take actions that have the best chance of achieving a specific goal. The technology is evolving continuously to benefit many different industries and being scrutinized for its positive and negative consequences. Today, due to the rise of big data and improvements in computing power, AI has entered the agriculture and allied fields as well. Relatively speaking, Agriculture has been one of the sectors that has a slow adopting tendency for AI (Nuthall and Old, 2018).

Being a vast field with many applications, AI is also one of the most complicated technologies to work on. Machines inherently are not smarter; a lot of computing power and data are required to empower them to simulate human thinking. A set of technological and scientific advances have led to the growth in the use of AI in real-world applications in various fields due to the tremendous increase of data with high computational power and large storage to empower them to simulate

human thinking. It is possible that a machine to learn from its experience by adjusting their responses based on new inputs provided, performing the human-like tasks. The machines can be trained to process a large amount of data and recognize a pattern in them. Finally, AI is a data-processing system or computational systems that take data as inputs and process them to lead to a user-friendly output (Gadanidis 2017; Figure 1).

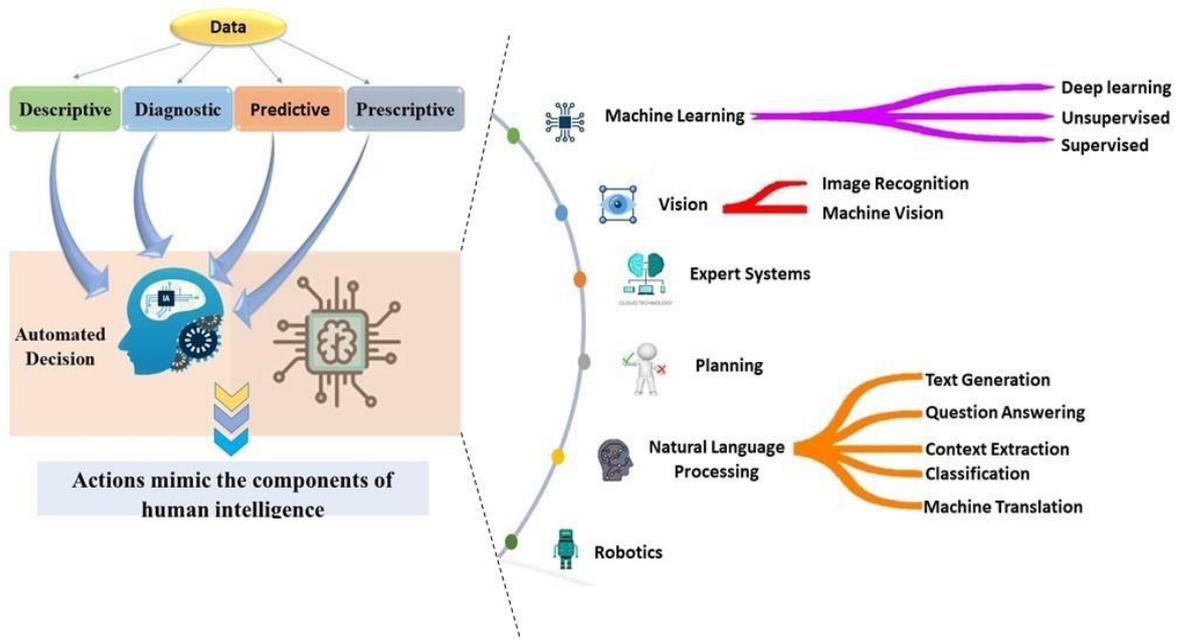


Figure 1. Converting data into actionable decisions through different fields of artificial intelligence (Source: Authors' creation)

Considering its characteristic features, AI can be further classified into a number of sub-fields (Min, 2010), namely, machine learning (ML) and expert systems (acting humanly), artificial neural networks (ANN; thinking humanly), fuzzy logic (thinking rationally) and agent-based systems (acting rationally). Many of these are working together in applications. Despite the anticipated improvements associated with AI, its potential is still not fully utilized in the context of food security as compared to other sectors such as IT, transportation, economics, social media, and businesses. As a result, challenges of technological

innovation and impacts of AI still remain underexplored.

Therefore, the intent of this paper is to provide a detailed account of the importance and use of AI applications in relation to four pillars of food security, focusing on key AI trends that can impact the agriculture and food security sectors in Sri Lankan context. This article examines and highlights the ways in which AI technologies can revolutionize the agriculture and food sector in Sri Lanka.

### Artificial intelligence in achieving food security

#### Food availability:

Ensuring food availability is directly related to enhancing global food production. Increasing both the crop and animal productivity and land productivity in a sustainable manner are thus,

important approaches while reducing the losses. This effort is faced with many challenges, which predominantly includes pest and disease infestations, inadequate and improper application of agrochemicals, improper drainage and irrigation,

weed control, yield prediction and many more (Pinstrup-Andersen, 2009; Bannerjee *et al.*, 2018). In this section, we focus on applications of AI techniques on different aspects of crop, animal and aquaculture production systems, which would enable enhanced food availability.

*Crop management systems:* The concept of using AI in general crop management goes way back to 1980s. Lemmon (1986) first proposed the idea identifying the same as "Expert Systems for Agriculture". Since then, many computer researchers have come forward with their ideas in this regard. Robinson and Mort (1997) proposed an Artificial Neural Networks (ANN) to predict the occurrence of frost in the Italy's island of Sicily that would harm the much important citrus [*Citrus limon* (L.) Burm] cultivation in the island. Prediction of overnight frost through ANN has been extremely accurate and successful over a long period. Li *et al.* (2002) proposed an image-based AI management system for a wheat (*Triticum aestivum* L.) crop by using pixel labeling algorithms for image strengthening.

In India, a soybean [*Glycine max* (L.) Merr.] crop management system has been developed using fuzzy logic technology, having the capacity to advice the farmer regarding crop selection, fertilizer application and pest related issues with much more accuracy compared to available crop modelling packages (Prakash *et al.*, 2013). Crop management systems for protected agriculture can be designed with the help of AI technology. With the increasing worldwide demand for fresh and healthy foods, there is more emphasis on greenhouse technology to increase its production. However, finding skilled staff to manage such sophisticated facilities is increasingly becoming a challenge.

*Soil and irrigation water management:* Proper management of soil and irrigation is vital for agricultural production. With continuous large-scale, mono-cropping being practiced in agriculture over a long period, soil degradation in many arable areas has become a harsh reality.

Athani *et al.* (2017) has designed a soil moisture monitoring system using Internet of things (IoT) enabled with arduino sensors for optimum soil and irrigation management for the pasture growers in North-Karnataka, India. The authors have used information received from the input sensors, which

are handled using the neural networks algorithm and correction factors for monitoring. With the use of simple, accessible components, the technology has vastly decreased the manufacturing and maintenance costs, making the system more affordable for the small-scale farmers in rural areas. Arif *et al.* (2013) has developed a similar system for irrigation management in paddy fields and proposes an ANN model to estimate soil moisture in paddy fields with limited meteorological data. They have used reference values of evapotranspiration and precipitation for this model. Land leveling can be identified as one of the most important operations in paddy cultivation that improves the water-coverage uniformity in the field, thereby improving the irrigation efficiency (Di, 1999). Si *et al.* (2007) were able to develop a fuzzy-based, laser leveling system for land leveling purposes, comprising a laser transmitter, laser receiver, controller, hydraulic system and a bucket. Fuzzy-based system in the controller allows the machine to judge the position of the bucket, indicating the height of the field, which is integral to the working mechanism of the leveler.

Assessment of plant water status is vital for designing irrigation schedules in modern agriculture. However, with old techniques, it can become a tedious and a labor consuming task. Valdes-Vela *et al.* (2015) were able to design a soft computing technique to develop a model, which is capable of estimating stem water potential of plants using soil water content and meteorological data. As this system uses fuzzy rules, its' out-puts have greater approximation power. Risk assessment and characterization of contaminated soils presents a great challenge for soil scientists worldwide. Lopez *et al.* (2008) have developed a classificatory tool applied to characterize contaminated soil using fuzzy logic. This belongs to the category of AI based Decision Support Systems (DSS). Elasticity of fuzzy set formalism provides an improvement in deviations and variance of the data, giving greater accuracy for these systems over typical computer-based models.

*Insect pest and disease management in crops:* Insect pest and disease control of crops is of vital importance in order to increase the yields and thereby production. It has been estimated that the crop yield losses caused by various pests and diseases for most important food crops are 20-40% and 40%, respectively, in each year (AGRIVI, 2020). All the aspects of insect pests and disease control

require significant amounts of human experience and expertise and this is a major limiting factor for agricultural production. Insect pest and disease control are primarily practiced using various forms of pesticides. Those pesticides possess negative effects on the environment and human health, hence paved the way to find out eco-friendly methods. Therefore, this has grabbed the attention of both agriculturist and computer scientists over the last few decades and they have been able to come up with various solutions.

In order to detect biological objects on a complex background, scanner image acquisition, sampling optimization and advanced cognitive vision have been combined. Thus, the system has been integrated with extensible knowledge-based systems for image analysis and natural object recognition, which was coupled with image processing programs and ML (Boissard *et al.*, 2007). Bestelmeyer *et al.* (2020) developed an AI-based tools that manage site-based scientific data and big data in the effort to scale up agricultural research with artificial intelligence with a view to help farmers and land managers make site-specific decisions. These tools provide early-warning of pest and disease outbreaks and facilitate the selection of sustainable cropland management practices.

Peixoto *et al.* (2015), developed an approach via fuzzy systems for understanding the population dynamics and control soybean aphid (*Aphis glycines*). They used fuzzy sets theory-based methodology to describe the interaction between the soybean aphid and its predator, *Orius insidiosus*. This model, considering all the biotic and abiotic factors, proposes a chemical control for the soybean aphid, and has been useful in predicting the timing and release of predators for the biological control of soybean aphid. Success of an Integrated Pest management (IPM) program largely depends on knowledge and information related to every aspect of the crop-pest system. Siraj and Arbaiy (2006) proposed an IPM program (FuzzyXpest) using fuzzy expert system to provide information related to insect pest activities in Malaysian rice (*Oryza sativa* L.) fields for farmers and researchers instead of mathematical model which are imperfect and makes uncertain in most of the cases.

Insect pest management in tea [*Camellia sinensis* (L.) Kuntze] cultivations is a major challenge faced

by the growers. Lack of human expertise to cover a wide area of tea cultivations is the major issue. Ghosh and Samanta (2003), developed an expert system for insect pest management in tea in order to address this issue of lack of human expertise. This rule-based, object-oriented expert system, code named "TEAPEST®" has been extremely useful and supportive for the tea experts in India over the years. Another similar fuzzy logic-based, decision support system (DSS) to control insect pests in olive (*Olea europaea* L.) cultivations have been developed by Jesus (2008). He has combined open-source Geographical Information System (GIS) like GRASS-GIS, Map server, and the computer languages (Perl and PHP) in order to design this flexible DSS that supports IPM in olive culture.

Boissard (2008) has presented a strategy based on advances in automatic interpretation of images, which has been applied to detect mature whiteflies (*Trialeurodes vaporariorum*) on rose leaves. There system was integrated with extensible knowledge-based systems for image analysis and natural object recognition, which was coupled with image processing programs and ML. This system illustrates the collaboration of complementary disciplines and techniques, which has led to an automated, robust and versatile system. This was reliable for rapid detection of whiteflies. This study was done to automate the operations in green houses. Some of the earlier rule-based computer systems include the expert system for diagnosis of potato (*Solanum tuberosum* L.) diseases by Boyd and Sun (1994), and the expert system for diagnosing diseases in rice plant by Sarma *et al.* (2010). Later, with the advancement of AI technology, different ANN based systems have been developed with extremely promising results. Karmokar *et al.* (2015) has developed a tea leaf disease recognizer using the ANN technology. They take an image of the tea leaf and use a neural network ensemble for the pattern recognition of the tea leaf in order to identify the disease.

Sladojevic *et al.* (2016) suggested a new approach in image processing that would lead to a smoother disease identification. Their method is based on leaf image classification, by the use of deep convolutional networks. Kolhe *et al.* (2011) developed a new approach in diagnosis of diseases of the oilseed-crops using a web-based intelligent disease diagnosis system (WIDDS®). It is based on a new fuzzy logic approach. Inference drawn from this method are much faster than those from the

earlier methods. This system has been tested for three oilseed crops, namely, soybean, groundnut (*Arachis hypogaea* L.) and rapeseed-mustard (*Brassica napus* L.).

Hahn *et al.* (2004) suggested and developed a method of Spectral Detection and Neural Network Discrimination of *Rhizopus stolonifer* spores on red tomatoes [*Solanum lycopersicum* (L.) H. Karst]. *Rhizopus stolonifer* is responsible for about 80% of the total loss in pre-packaged tomatoes. Hence, this method has been extremely effective in this regard. Boyd and Sun (1994) revealed the potential of expert system (ES) use in managing the disease component of potato seed production.

Usually, free moisture is consumed by fungal and bacterial plant pathogens for the infection and reproduction; accordingly. Therefore, the wetness duration on plant surface should be estimated to use in the disease forecasting model if the directed measurements are not available. An ANN model with back propagation architecture can be used to predict wetness on flag leaf of wheat by recording the environmental variables using an electronic data logger (Panda, 2020).

*Weed management:* Weeds affect the quantity and quality of crop yield and thereby, food availability. Chemical control is the most commonly adopted method of weed management in many agricultural fields. Nevertheless, excessive usage of herbicides over a long period of time can be harmful to both humans and on the environment. Identification of the weeds in the field itself is one of the integral parts of weed management. However, AI methods can be used in an effective way to minimize the application of herbicides in agricultural fields by selective destroying. Already, promising signs in this regard are apparent in the field of computer science.

Tobal and Mokhtar (2014) developed an AI-assisted image processing method to successfully identify weeds in the field. They have introduced an evolutionary ANN in this system. Through optimizing the neural parameters by means of a genetic algorithm, this system can minimize the time of classification-training and operational errors. Many similar AI-assisted weed identification and classification systems have been developed during the past two decades. Most of these systems have used the ANN technology (Eddy *et al.*, 2008; Barrero *et al.*, 2016). There is a huge

potential for weed monitoring through unmanned aerial vehicles (UAV). Perez *et al.* (2016) have developed a novel strategy for weed management through the combined use of UAVs, image processing and ML. The UAVs provide an ultra-high spatial resolution as opposed to the poor temporal and spatial resolutions of most of the old school remote platforms such as piloted planes and satellites. As a result, this technology provides great promise, especially in the area of early post-emergence weed control.

*Plant breeding:* Advances in breeding for food crop improvement will be basically responsible to tackle food insecurity in the future, while enabling food availability by producing high yielding cultivars and safeguarding the harvest. Genetic breeding programs have provided new cultivars with desirable traits, such as high yield, yield stability in changing climatic conditions, increase tolerance to abiotic stress, nutrient use efficiency, disease resistance, and quality (Chiorato *et al.*, 2010; Harfouche *et al.*, 2019; KWS, 2020).

Assessment based on a set of yield data comprising thousands of observations of cultivars with a variable response to weather conditions suggested that current breeding programs do not sufficiently prepare for climatic uncertainty (Kahiluoto *et al.*, 2019). Crop breeders still struggle with tradeoffs such as higher yield, marketable appearance and future needs with climatic uncertainty and variability. To overcome these challenges, turning to AI technologies is being promoted. Using computer science techniques, breeders can rapidly evaluate which plants grow best in a particular climate, which genes help plants thrive there, and which plants produce an optimum combination of genes for a given location when crossed, opting for traits that boost yield and hold off the effects of a changing climate (Beans, 2020).

The ANNs have been used for plant breeding, including use in the investigation of genotype x environment interactions. Correa *et al.* (2016) have developed an ANN method as an effective alternative to measure the adaptability and phenotypic stability of genotypes in breeding programs in Common bean (*Phaseolus vulgaris* L.). In this regard, the simulated genotypes are used to train and validate neural networks. As ANNs can capture more complex features of data sets, detailed information about the method is not required to be modelled due to its self-learning.

Ampatzidis and Partel (2019) has developed a technique for data acquisition and image processing using small UAVs, multispectral imaging, and deep learning convolutional neural networks to evaluate phenotypic characteristics on citrus crops. This phenol-typing technique utilizes AI and ML to detect, count, and geolocate trees and tree gaps, to categorize trees based on their canopy size, to develop individual tree health indices, and to evaluate citrus varieties and rootstocks. This UAV-based technique provides a consistent, more direct, cost-effective, and a rapid method to evaluate phenotypic characteristics of citrus varieties and rootstocks.

Image analysis using proximal sensors can help to accelerate the selection process in plant breeding and also to improve breeding efficiency. However, the accuracy of extracted phenotypic traits, are highly affected by the pixel size in images. In developing new varieties, breeders often aim for rapid ground coverage (GC) estimation, which is challenging. Hua *et al.* (2019) used a classification based on a machine-learning model to classify pixels of original images. Such images are often captured using visual-spectrum cameras on multiple platforms. The corresponding degraded images into either vegetation or background classes would help in computation of their GCs.

*Crop yield prediction:* Accurate crop yield prediction is a powerful weapon to improve food production. It prepares all players in a food system for what is to come. It is also beneficial for cost estimations and marketing strategies as well. The AI technology can play an important role in yield predictions in the future.

Kaul *et al.* (2005) developed an AI system using ANN for corn and soybean yield prediction. Models for yield prediction were developed using historical yield data at multiple locations. Reports show that these ANN models did produce more accurate predictions compared to those from regression models. Similar system has been developed by Ji *et al.* (2007) for rice yield prediction using ANN technology. This system was developed for the Fujian province of China, where adverse weather conditions such as typhoons, floods and droughts threaten rice production. They have used location specific historical weather data for the development of the model. This ANN model, too, has proven to be more accurate than linear

regression models for the yield predictions in the Fujian province.

Few more similar ANN models have been developed for yield prediction in cotton (*Gossypium hirsutum* L.) (Zhang *et al.*, 2008), wheat (Ruß *et al.*, (2008), Jute (*Corchorus capsularis* L; Rahman and Bala, 2010) and tomato (Ehret *et al.*, 2011). Apart from directly predicting the yield, ANN models are capable of capturing other variables that are impactful on agricultural production. Nabavi-Pelesaraei *et al.* (2016) developed an ANN model that is able to predict the energy usage and greenhouse gas (GHG) emission from watermelon (*Citrullus lanatus* L.) production systems. Such predictions will surely benefit the future farmers and would inevitably improve the food availability for the future consumer.

*Livestock production:* Livestock sector also plays a major role in producing food for the world population. Meat, milk and eggs are main food types comes from livestock sector. Application of AI can improve the productivity and efficiency in the sector. Use of Robotic or automatic milking systems has increased with the time in dairy farming in the United Kingdom, Europe and in North American. Robotic milking machines have been introduced to perform milking without any intervention of human workers (Butler *et al.*, 2012) finding solution for labour scarcity. Use of AI in automatic milking has increased milk yield by 5-10% due to increased milking frequency (Broucek and Tongel, 2017). It may lead to an increase in milk availability while helping in achieving food security in the future. In the automatic milking systems, the Fuzzy logic algorithm (Kamphuis *et al.*, 2008) has been used to identify the mastitis in milking cows. ML fitting models are also used to predict milk yield, fat and protein contents, and actual cow concentrate feed intake (Fuentes *et al.*, 2020). Those predictions have helped improving the milk production while cutting down the additional costs.

The ANNs have been applied to determine chemical quality and composition of meat, in efforts to evaluate sensory quality such as tenderness, color, marbling score, water holding capacity (Suzuki, 2011). The ANNs have helped in assessing meat properties based on digital images of meat surface (Li *et al.*, 1999; Lu *et al.*, 2000), based on near infrared spectra (Prevolnik *et al.*, 2009), mass spectroscopy (Sebastian *et al.*, 2004), hyperspectral

imaging (Qiao *et al.*, 2007), or ultrasonography (Brethour, 1994).

Many studies have been done on classification or carcass quality evaluation in bovine carcasses (Borggaard *et al.*, 1996), lamb (Chandraratne *et al.*, 2007), and goat (Peres *et al.*, 2010) using ANN. Ellis and Goodacre (2001) identified spoilage using biosensors, electronic noses, and infrared spectroscopy, which are upgraded with ML methods such as ANN with genetic algorithms.

*Animal breeding:* Animal breeding is a key factor to increase livestock production and the genome prediction is a major application of ML in the animal breeding sector. Machine-learning methods aim at improving a predictive performance measure by repeated observation of experiences. Further it has performed better than the Bayesian regression method in genome prediction (Gonzalez-Recio *et al.*, 2011). Genome-wide prediction of complex traits has become increasingly important in animal breeding. The ANN, Support Vector Machines (SVM), and random forests and boosting have been used for genome-enabled prediction in livestock (Gonzalez-Recio *et al.*, 2009; Long *et al.*, 2011). However, ML approaches provide a larger and more generally suitable flexible methods for genome-wide prediction (Gonzalez-Recio *et al.*, 2014).

Furthermore, ML methods can be used for predicting animal body weights from camera images rather than using a weight scale, which is laborious, time-consuming and causes stress on animals. Furthermore, these methods can be used to predict carcass composition from on-line camera images in real-time (Neethirajan, 2020). This is also important to improve animal breeding as this method can be applied to check the phenotype quality that would make a perfect animal breeding process. Morota *et al.* (2018) showed that these ML models are successful in identifying outliers in the data and can be applied to filter and edit data prior to genetic evaluation.

*Animal health management:* Automatic milking systems have been used in the identification of clinical mastitis with the use of electrical conductivity sensors (Khatun *et al.*, 2017) because mastitis infection alters the concentration of anions (Na<sup>+</sup>) and cations (Cl<sup>-</sup>) (Kitchen, 1981). This ion alteration occurs due to altered milk pH, temperature, and leakage between secretory cells

(Mucchetti *et al.*, 1994). Automatic milking systems also have a potential to detect the udder health, reproductive status, feed intake, and body weight changes. Consequently, individual animals are monitored with greater details. This directly improves the production and quality of the final product (Jacobs and Siegford, 2012).

Attached and non-attached sensors are devices to determine behavioral and physiological parameters in order to identify disease conditions such as mastitis, fertility problems, locomotion problems and metabolic problems. Data produced by sensors are processed by a data algorithm. The output of this algorithm can be seen as either general information of the herd health for the farmer or additional data input for the detection algorithm. The decision is eventually made either by the farmer or autonomously by the sensor system (Rutten *et al.*, 2013). Moreover, AI technologies are used to produce vaccines against various kinds of diseases. According to De La Fuente *et al.* (2018), intelligent big data analytic techniques used to predict the correct protective antigens have provided solutions to produce vaccines for prevention and control of tick-borne diseases.

The clinical disease neosporosis that linked with abortion of cattle caused by protozoan parasite *Neospora caninum* has resulted in a huge economic loss worldwide (Anderson *et al.*, 2000). In order to overcome the limitations in the traditional approach of producing vaccines to prevent the disease, ML algorithms have been introduced. It works with current data and identifies potential candidates for vaccines (Goodswen *et al.*, 2014). As the lameness causes reduction of production in the cattle industry, ML and data analytics techniques were introduced to identify lameness in cattle automatically and to isolate the animal or treat immediately to avoid any further effects of lameness (Byabazaire *et al.*, 2019; O'Leary *et al.*, 2020).

Facial recognition also used to monitor the behavior of animals. This may help to maintain good health throughout the herd (Neethirajan, 2020). Modern farms use a robotic injection system to deliver vaccines and for automated blood sampling. In this method hardware is automated by robotics and with the use of cameras, microcontrollers and sensors, robots get targeted

animal and administrate the vaccine (Rizvi *et al.*, 2005).

*Aquaculture production and disease control:* The ANNs have been used in forecasting, classification, and distribution in fisheries management and aquaculture systems. Forecasting in fisheries covers the distribution of eggs, recruitment, fish growth, biomass and fish catch (Suryanarayana *et al.*, 2008). The AI plays a significant role in reading the fishes through vibration-based sensors and acoustic signals. This will help in differentiating a hungry fish from that of a full. An Indonesian aquaculture intelligence company known as 'eFishery' has recently developed an AI feed dispenser, which releases the right amount of feed at the right time. In aquaculture, wastage of inputs can be managed through AI and cost can be reduced up to 30%. Thus, AI provides complete control over the fish producing systems with less maintenance and reduced input cost (Jothiswaran *et al.*, 2020).

The AI has been used to prevent diseases in aquaculture through the smartphone applications that assist farmers in testing water quality and predicting diseases. Mobile applications called 'FarmMOJO®' helps shrimp farmers to analyze water quality and predict diseases. Through these applications, farmers can prevent diseases even before the outbreak starts (Jothiswaran *et al.*, 2020). To prevent a disease outbreak, Norway's seafood innovation cluster launched a project called 'Aquacloud' in April 2017 (Jothiswaran *et al.*, 2020), which is a cloud - based program that helped farmers in preventing development of sea lice in cages. This reduced fish mortality and minimized dependency on more expensive treatments.

The Aquaculture Research Institute of the Kindai University in Japan is using Microsoft azure ML studio to identify and remove odd-shaped fish seed from the rearing cage (Jothiswaran *et al.*, 2020). Through satellite and AI programs, fishing vessels can be monitored by image recognition and automatic review of video footages. This will help reducing IUU fishing (Marzuki *et al.*, 2017).

#### Food accessibility

One of the most important responsibilities of a society is to ensure that all people have adequate access to food. However, deficiencies in food production or inefficiencies in food distribution

systems or both have made it difficult to maintain the equity. The AI technology has been recognized as an application to increase the efficiency in food value chains (Di Vaio *et al.*, 2020). For an equal and efficient food supply, it would be important to identify the areas with inadequate access to safe and nutritious food. Regions with insufficient spatial and socioeconomic access to nutritious food are named as food deserts (Widener and Shannon, 2014). In a recent study, big data analytics and ML have been used to develop a food desert identifier that traces areas with inadequate food access in Cuyahoga County in the United States (Yiyuan, 2020). Amin *et al.* (2020) had utilized ML to develop the optimal models using data from U.S.A. census tracts that can predict access to healthy food with high precision. Their model identifies food deserts and food swamps with a prediction accuracy of 72%.

The factors related to agriculture supply chain are greatly uncertain, including the proper storage and transportation of perishable agricultural products. Models based on fuzzy execute better when addressing such real-time uncertainty (De and Singh, 2020). Liu *et al.* (2019) developed a fuzzy decision tool to assess sustainable performance of agriculture-food value chain. The model integrates triangular fuzzy numbers (TFN), analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) in a novel way to consider quantitative and qualitative criteria. The fuzzy decision tool evaluates the sustainable performance of suppliers according to the economic, environmental and social aspects.

Forecasting of food production and consumption would help in logistical planning of the existing resources nationwide. A study done by Sharma and Patil (2015), had used a fuzzy inference system to forecast the production and consumption of rice yearly while Yan *et al.* (2015) employed four ML techniques, namely, ANN, support vector machine (SVM), genetic programming (GP), and Gaussian process regression (GPR), to develop a feasible and economical tool to forecast future milk yield at the individual cow and the group level. Evolutionary machine learning (EML) techniques can find solutions to reduce time and cost for both production and transportation. Supply chain optimization has been done using EML methods to reduce held-inventory and cost in supply chains of food industry (Cheraghalipour *et al.*, 2018), and being widely applied for transportation scheduling

of milk and seafood products (Sethanan and Pitakaso, 2016). Liu and Hue (2017) combined the neural network algorithm, classification regression tree algorithm, and bayesian network algorithm to estimate the results of and monitor perishable food transportation metamorphism (Liu and Hu, 2017).

Proper access to food becomes more crucial in pandemic situations like COVID-19. Thus, it is important to ensure safe distribution of food and essential supplies to all citizens to sustain them through challenging times. Sharma *et al.* (2020) have proposed a robotic drive through system, which can be used to achieve this objective. It is an affordable and contactless robotic system for organizing and dispensing food and survival kits at community scale. The system also has enabled to prevent hoarding and price gouging. Cargo-bearing UAVs have great potential to assist in delivering food, medicine, and other supplies. Faust *et al.* (2017) have proposed an autonomous aerial cargo delivery instrument that works in environments with static obstacles. Another study has reported a prototype architecture employing IoT devices for monitoring food deliveries (Markovic *et al.*, 2019).

#### Food utilization

Food utilization involves food safety and quality, the quantity of food a person eats, and the efficiency of conversion of food to energy inside the human body. Among them, the quantity of food a person eats and the efficiency of conversion depends on the person. Therefore, food safety and quality is the one that can be used to achieve food security in general under the aspect of food utilization. Food safety and quality highly depend on postharvest handling practices, food storage, and processing techniques. The AI can be successfully used to enhance food security by improving these practices and techniques.

The postharvest losses can be defined as the losses that occurred in terms of quality and quantity of crop products after the harvest till the consumption (Kader, 2013). During postharvest storage, degradation of the quality of agricultural products refers to weight loss, changes in colour, visual quality nutrient content and, flavor, etc. Postharvest losses make food unsafe to consumers. Biological (respiration, transpiration, ethylene, and postharvest diseases) and environmental factors (temperature, relative humidity, atmospheric composition, and light) affect the deterioration of harvested produce (Kahramanoglu, 2017). The AI

will help achieving food safety and quality by controlling those biological and environmental factors. Babawuro *et al.* (2015) proposed an intelligent temperature control technique for fresh cassava roots postharvest storage system using a fuzzy logic controller. where the storage temperature is controlled by simulating two inputs (error in temperature and rate of change in the error) and one output (change in fan speed). A fuzzy controller for fruit storage using neural networks and genetic algorithms was introduced by Morimoto *et al.* (1997), where the relative humidity in the storage house is maintained at a desired value through the on-off control of ventilation by the fuzzy control. Gottschalk (2003) introduced an improved, energy-efficient climate control system for potato storage houses using fuzzy controllers.

Most of the fruits and vegetables are highly affected by brown spots and bruises as a result of mechanical stress during postharvest handling. It makes unpalatable and spoiled leading insecure the food to consumers. Therefore, it is important to detect during the early stage. Otherwise, the whole consignment would be affected. The mechanical damage can be detected early using Near-Infrared (NIR) hyper-spectral images and ML, which is one of the applications of AI in fruits such as mango (Rivera *et al.*, 2014), strawberry (Nagata *et al.*, 2006), citrus fruits (Qin *et al.*, 2011) and apple (Huang *et al.*, 2013). Borrás *et al.* (2011) indicated that the hyper-spectral imaging technique can be successfully used as a tool for the automatic inspection and monitoring of internal defects of fruits and vegetables in postharvest quality control laboratories.

After harvesting, assorting of fruits and vegetables is compulsory to meet the quality evaluation criteria as consumers are becoming more and more cognizant of food quality and safety. With the aid of AI, this process could be made faster, reliable, and labor inexpensive. Some researchers in USA state that, for every robot added per 1,000 workers, wages decline by 0.42% and the employment-to-population ratio goes down by 0.2 percentage points (MIT, 2020). Computer vision and deep learning methods-based approaches together with image processing techniques have been developed for apple (Sofu *et al.*, 2016; Valdez, 2020), tomato (Irerri, 2019), banana (Larada *et al.*, 2018), date fruit (Al Ohali, 2011), potato (Przybylak *et al.*, 2020) to

detect healthy fruits and vegetables from those with defects.

Consumers always expect to have fresh agricultural products with higher nutritive and sensory value. When industries are keen on achieving this task, they have to face the challenge of insect infestations. The non-destructive, advanced technologies related to AI have been introduced to overcome this challenge (Adedeji *et al.*, 2020). Visible light sensors at the wavelength range from 380 to 750 nm had used to detect external or surface features of fruits and vegetables (Liu *et al.*, 2017). This technique has been applied with the aid of ML technique to detect insect infestations such as scale insect in citrus fruits (López-García *et al.*, 2010), thrips in citrus fruits (Blasco *et al.*, 2009), medfly in citrus fruits (Blasco *et al.*, 2016) and insect damages in pistachio (Pearson *et al.*, 2001).

While visible light sensors are applicable for surface detection of insect infestations, the Hyper Spectral Imaging system can be applied to accurate detection of hidden internal damage from insect infestations without sample destruction (Adedeji *et al.*, 2020). For instance, this concept together with ML techniques has been applied to detect codling moth in apple (Rady *et al.*, 2017), fruit fly in jujube fruits (Liu *et al.*, 2016), and pod borer in soybean (Ma *et al.*, 2014).

Food processing turns fresh foods into food products while making them edible, increasing shelf life and safety, and ensuring nutritional quality. Food security may be highly affected at food processing as a result of contamination of food due to handling by humans. Robotics driven by artificial intelligence can be successfully used to get the labour force for food processing activities to achieve food hygiene (Iqbal *et al.*, 2017). Nowadays robotics are highly used to automate food processing applications such as pick and place, cutting and slicing, cleaning to maintain safe working environments, and vision-guided sorting robots (RIA, 2020).

Drying is the primary method of food preservation. It increases the shelf life of food products by lowering the moisture content. A lot of methods such as hot air drying, vacuum drying, freeze-drying, heat pump drying, superheated steam drying, and microwave drying are being used in the industry depending on the requirement (Zielinska *et al.*, 2013). Despite the method, drying conditions

should be optimized to achieve the desired shelf life, quality, and safety of the food products. Manually control of those conditions is very hard and sometimes it would be impossible. The AI-based techniques can be successfully used to automate those conditions. Computer vision is highly applied in the food industry as a fast, reliable, and non-destructive method to automate the drying process by controlling the conditions such as temperature (Chen and Martynenko, 2013), power intensity (Barzegar *et al.*, 2015), airflow velocity (Shahabi *et al.*, 2014), pretreatment (Nadian *et al.*, 2016) and browning components (Gao *et al.*, 2017). When the drying process is very complex, nonlinear, and dynamic, artificial biomimetic technology which is a method of odor sensing system (electronic nose) and taste sensing system (electronic tongue) are increasingly deployed (Xu *et al.*, 2017). Raghavan *et al.* (2010), designed a real-time aroma monitoring system to control a microwave drying process using electronic nose and fuzzy logic algorithm.

Grading of agricultural products is one of the most important application in food processing as it highly contributes to ensure the food quality in processed foods. Manual grading is inconsistent, time-consuming, and leads to contamination as well. Therefore, automated grading is more superior to manual grading. The acidity of pomegranate determines its uses satisfying the needs and tastes of consumers.

Considering this fact, Fashi *et al.* (2020) designed a model to grade the pomegranates based on pH, using three algorithms of AI such as adaptive neuro-fuzzy inference system (ANFIS), ANN, and response surface methodology (RSM). The best results were obtained by using the ANFIS model. Larada *et al.* (2018) introduced a fruit classification system for banana using ML and graded fruits into four classes such as extra class, class 1, class 2, and class 3. They were able to achieve 97% accuracy ignoring the reject class. Thus, AI can be effectively implemented in the postharvest handling and food processing industry to ensure food security.

#### Food Stability

There are several challenges of food stability that are directly linked with food availability, food access and utilization. These challenges include, increasing the demand for quality foods and the quantity, adaptability to new and variable climates, pest and disease outbreaks. The AI can be used to

notice the climate influences and to improve the warning system of extreme weather events. The Earth System Model with the ML techniques can be used to understand the full climate system that has not occurred with the direct equation analysis or visualization of measurements (Huntingford *et al.*, 2019).

If food stability is to be achieved in the future, breeding programs must produce unprecedented increase in yield and resource-use efficiency while safeguarding harvests and preserving environment and ecosystem services. Plant breeders have a bigger responsibility to produce cultivars that have the capacity to buffer against climate-related uncertainty and variability, increase in tolerance to abiotic stress, nutrient use efficiency, pest and disease resistance, as well as quality (Carpenter *et al.*, 2011; Harfouche *et al.*, 2019; KWS, 2020).

High dimensional phenotypic trait (phenomic) data with a ML approach provided support to do season seed yield prediction and prescriptive cultivar development for targeted agro-management practices (Parmley *et al.*, 2019). Different ML approaches can be deployed to identification, classification, quantification and prediction. Those data used to implement rapid plant breeding program (Singh *et al.*, 2016).

These dimensions have to cope-up with the altered weather patterns and ML. One of major impact of climate change is global water scarcity driven by the heterogeneity of consumption distribution and the available of seasonal water (Mekonnen and Hoekstra, 2016). Spatial distribution of the water resources and the irregular climate change impacts are related to the geographic locations (O'Neill *et al.*, 2017). A suitable way of water resource management may be a distributed network approach using blockchain technology for a decentralized immutable community water transactions record (Lin *et al.*, 2017). Blockchain data securitization protocols come together with AI algorithms trained by remote sensor water data to

distribute water. This technology can yield advantages in scarcity pattern identification and efficient water abundance for equitable multi-scale water resource management under climate change conditions (Lin *et al.*, 2018). Hydrodynamic model and the neural network used to minimize the ground water overexploitation and groundwater remediation through pump-treat-inject technology using optimum control by AI (Sadeghfam *et al.*, 2019; Hani *et al.*, 2006). According to Hani *et al.* (2006), ANN showed a spring flow decrease not only due to the unfavorable climatic condition, but also due to the intensive exploitation of the aquifer. Thus, these results have revealed that ground water reserves are decreasing over time. Hence, this analysis would help taking urgent measures to stop intensive exploitation of the aquifer that would indirectly affect the stability of the continuous food supply chain.

Plant and animal diseases would directly affect food stability, too. The AI applications in crop, livestock and aquaculture disease management have been discussed in the food availability section of this article. To maintain the fish supply chain stability, disease management, fish seed screening, end-to-end traceability when products are exported, and routine checkup of stocks are frequent requirements. Furthermore, prevention of illegal, unregulated, unreported (IUU) fishing is a key factor in achieving the stability of food supply to avoid over-exploitation threatening the continuous food supply chain.

The AI technology is used to overcome those problems and to thus, to save money, time and labour use (Suryanarayana *et al.*, 2018). The traditionally used supply chain quality data integration methods cost a lot in integrating product quality, however, the integration accuracy is low and the effectiveness is poor. A supply chain of agricultural products has been set up based on the AI integration method of block chain using quality data (Wang, 2019) to enhance the system effectiveness and lower operational costs.

## **How Sri Lanka can be benefited from artificial intelligence in achieving food security**

Food security in Sri Lanka is threatened by growing population, with slow but steady annual population growth rate of 1.1% (AgStat, 2019). In Sri Lanka, there is a vast agricultural diversity due to the variability in climatic conditions and soil types

within the country. Moreover, agriculture is the livelihood of the majority of people, the contribution of agriculture sector (primary production only) to the GDP is diminishing over the past years and was 7.42% in 2019 (DCS, 2020).

Increasing population, climate change, yield gaps, crop losses, and low attraction of the younger and skilled generation to farming, are the challenges that country experiences, threatening food security (Marambe *et al.*, 2015; Esham *et al.*, 2018; Withanage, 2019).

Rice is the staple food (cereal) in the country and, around 65% of the total population directly or indirectly involves in paddy farming. With the increasing population in the country, the rice production needs to be increased at the rate of 2.9% per year to meet the demand in 2050 (AgStat, 2019). In 2018, Sri Lanka has spent Rs. billion 422.5 to import food and beverages accounting to about 11.8% of the total imports to the country (DCS, 2020). Being a country with the capacity and high potential to produce the requirement of our main food crops, Sri Lanka still produces only about 69% of maize, 10% of big onion, 58% of cowpea, 84% of groundnut, 49% of black gram and 80% of red onion, as of 2018, and is heavily dependent on food imports to feed our nation (Marambe and Silva, 2020).

Therefore, the new technological adoptions have become crucial for the sustainability of the agriculture sector and thereby food security in the country. As many other countries, Sri Lanka is still goes through slower adoption phase of the new technologies including AI. There are very few applications that have been recorded recently as research initiatives in the use of AI in agriculture, *i.e.* application of ANN to predict paddy yield using climate data (Amaratunga *et al.*, 2020), to develop pedotransfer functions for Sri Lankan Soils (Gunarathna *et al.*, 2019) and, development of an Intelligent Chat-Bot to provide solutions to the prevailing issues related to farming (Ekanayake *et al.*, 2020).

Sri Lanka Association for Artificial Intelligence (SLAAI) is currently operating as an AI research group in Sri Lanka. The main objectives of SLAAI are to increase public awareness of AI, to improve teaching and research in AI, and also to promote industry- academia partnership in the use for AI techniques for the real-world problem solving. The main activities of SLAAI include conducting of AI promotional programs, conducting of short courses in areas of AI, promoting research in AI, and conducting an annual AI conference. AI conference forms a stage to present and discuss the latest

research findings and applications in AI (SLAAI, 2020).

A draft policy framework to promote AI in Sri Lanka was unveiled by Sri Lanka Association of Software and Services Companies (SLASSCOM) in 2019 making good platform to have strong AI policy framework in the near future. The strategy comprehends seven objectives, namely, increasing awareness and adaptation of AI in both public and private sector, introducing regulations for a level playing field for AI, equipping society and people for the AI nation,

Showcasing AI's capabilities for the greater good, incentivizing fundamental and applied research in AI, identifying niche opportunities and attracting leading global technology and, AI companies to set up in Sri Lanka (Daily FT, 2020). As AI is a new concept in the country, still no agricultural related operations are being implemented, which is a limitation. Thus, stakeholders in the agricultural and allied fields of the country should work with the related organizations to access these new technologies to its sectors. The draft policy document of SLAASCOM also proposes setting up of a Centre of Excellence for AI either as a public-private partnership or as an independent body.

The AI technologies can be used in Sri Lanka in achieving food security in different ways particularly in the form of smart farming or precision agriculture. 'Smart farming' is a modern farm management concept that uses digital techniques to monitor and optimize the quantity and quality of agricultural products.

Today, many young and middle-aged farmers have access to an array of modern tools and data, ranging from low-impact information and communication technologies (ICT) to more advanced technologies such as the IoT, robotics and drones, blockchain, AI, big data, virtual reality (VR) and augmented reality (AR). Sri Lanka's large agri-business companies and emerging startup companies have already started popularizing drones, sensors, satellite image techniques and nanotechnology for farming operations. These could be used in smart agriculture to accurately measure the variations within a field and adapt strategically. These developments are likely to motivate young farmers and they will embrace these technologies as demand grows.

High cost of production, labour scarcity, sudden emergence of pest and disease outbreaks (e.g., Fall Army Worm – *Spodoptera frugiperda*), misuse of chemicals, correct identification of insect pests, weeds and diseases, accurate prediction of climate (drought, flash floods) and crop/animal yields, and streamlining transport, marketing, and storage facilities, are some of the major problems faced by the agriculture sector of Sri Lanka (Karunagoda, 2004; Esham *et al.*, 2018 Harees *et al.*, 2019; Perera *et al.*, 2019; Sumudunie and Jayasuriya, 2019; Perera and Rathnayake, 2019; Buhary *et al.*, 2020; Prasada, 2020). Nevertheless, AI can support practical applications to overcome those limitations.

Labour shortages in terms of number and the skills can be compensated by robots and other AI techniques such as ML (Rizvi *et al.*, 2005; Butler *et al.*, 2012; Iqbal *et al.*, 2017; RIA, 2020; MIT, 2020) especially in the food processing sector. Correct identification of insect pests, diseases and weeds would reduce the misuse of pesticides resulting in environmental sustenance. The AI applications such as, fuzzy logic systems, expert systems, ANN and ML have been developed to address these challenges with high precision (Ghosh and Samanta, 2003; Boissard *et al.*, 2007; Eddy *et al.*, 2008; Peixoto *et al.*, 2015). The climatic and yield prediction difficulties can be solved by using ANN

## COVID-19 Pandemic and the food security in the country

The recent COVID-19 pandemic has also reiterated the importance of food security particularly for developing nations. It has brought the global economy to a precarious position where Sri Lanka also has been impacted considerably at all levels. Almost all industries were negatively affected, apart from some essential services, such as water, electricity, fuel and those producing food (farming) and medical supplies. Continuation of food production as an essential service was a crucial decision taken by the authority in order to assure

## Synthesis and way forward

Use of AI in many fields supporting economies of many countries were evident over the past several decades. This can be viewed as a sign of new scientific order in near future, including that of food systems. As discussed in this article, achieving food security is the ultimate objective of future

models to forecast the climatic parameters such as, rainfall, relative humidity, temperature and wind speed (Perera and Rathnayake, 2019), and to understand the relationship with yield, thereby guessing forecasting the yield beforehand (Amaratunga *et al.*, 2020).

Streamlining transport, marketing, and storage facilities can be reached more efficiently and effectively by employing faster or simpler working methods in AI such as ANN, fuzzy logic systems, ML, computer vision and robotics. Forecasting production and consumption would help in making decisions, efficient food distribution and consequently supply chain optimization (Yan *et al.*, 2015; Sethanan and Pitakaso, 2016; Faust *et al.*, 2017; Liu *et al.*, 2019).

The issues related to post-harvest quality control in foods, particularly the detection of pests and diseases, and internal damages of products could be addressed through AI-driven food storage systems and preservation methods assist in restructuring the storage facilities (Morimoto *et al.*, 1997; Blasco *et al.*, 2016; Gao *et al.*, 2017). Therefore, the problems faced by the agriculture sector particularly in Sri Lankan context can be potentially addressed by using these ground-breaking technologies.

food availability and accessibility (Marambe and Silva, 2020). However, the food distribution took a longer time to return to normalcy. Under new normal situation, the working culture has now changed to the mode of “Work from Home”. Hence, there is a need to re-define the agriculture profession, and technological needs to achieve food security based on the new needs. In such context, we firmly believe that AI applications together with recent advancement in technology have a bigger role to play.

agricultural and allied sectors. A thorough review on the applications of AI in food security indicates promising signs in this regard. Within the food sector, AI could uplift existing practices and strategies in order to achieve productivity and sustainability goals efficiently and effectively.

As FAO (2008) clearly states, achieving food security relies on top of four key pillars. This article primarily focused on the applications of AI in these four vital areas of the food sector. There are many benefits of AI, which has been applied in the form of different tools and techniques that are user-friendly and providing optimum results. These techniques are combined with other technological advancements and being applied into agricultural practices along the food value chain. Many different AI technologies have been adopted over a wide range of applications in the agriculture sector in many countries. Among those, as expected, fuzzy logic systems, ANN and ML could be identified as the most frequently used technologies while being the pioneer concepts of this innovative branch of computer science. With the anticipated changes in trends in AI technology, we could expect differences in its complexion in applications in the future.

As indicated in Table 1, many applications can be identified on the use of AI in the area of food availability. This is directly related with the objective of improving food production. As it provides direct benefits to all the stakeholders, most of the AI technology developers seem to have concentrated their efforts in this direction. It would provide both short term and long-term benefits. However, achievement of future food security does not depend solely on ensuring food availability. One of the key findings of this review is the lack of AI applications in other three pillars of food security. Nevertheless, many recent developments indicates the use of AI applications towards other three pillars of food security as well. If this promising trend continues, there is expectations on the achievement national level food security and zero hunger objectives of the SDGs (SDG-2).

Countries in the developing world including Sri Lanka are however, way behind in adopting new agriculture related technologies, particularly the likes of AI. Unfortunately, there are not many studies and applications have been carried out on used of AI in agriculture. Nevertheless, moving away from conventional farming and towards tech-laden agriculture is a step on the right direction.

New technological transformation is essential for Sri Lanka's agriculture to reach its anticipated heights. It would largely invoke the countries' food sector, which is embattled with many challenges and constraints, such as lower productivity, downgraded product quality and disastrous impacts of climate change.

Sri Lanka, still being a developing economy, would face many challenges when incorporating AI technology to agriculture sector. Minimum awareness on the new technological developments among the stakeholders, fear of adopting new technology, restricted access to new technologies, and lack of government and institutional support for researching and adopting such novel technologies are some of the major constraints. Moreover, there are technical concerns. The AI technologies such as ML require big data in order for their optimal performance. Lack of accurate big data spanning over few decades is one of the major issues in this respect. Further, many agricultural lands in Sri Lanka are fragmented, resulting in smaller land parcel sizes, which should also be taken into consideration while adopting AI in the agriculture sector.

The rural and traditional farming community of Sri Lanka may not still be prepared to adopt these advanced technologies yet. Therefore, the government and private sector interventions are a necessity to use novel tactics to promote such technologies according to the farmers' requirements, such as public-private-producer partnership (PPPP) systems, shared platforms with all the stakeholders, and financing schemes and subsidised services to bring about this much needed technological transformation.

Research and development (R&D) through PPPP need to be focused on improving the use of such novel technologies and making them appropriate to Sri Lankan conditions. The AI and agriculture seem two vastly different sciences. However, the evidence provided in this article suggests that the marriage between these two fields of study could yield huge positive impacts in meeting the global goal of food security.

Table 1. A summary of AI applications in the four pillars of the food security

<b>Pillar</b>	<b>Application</b>	<b>Authors</b>	<b>Technique</b>	<b>Remarks</b>	<b>Practical use of the Application</b>
<b>Availability</b>	Frost occurrence predictor	Robinson and Mort (1997)	ANN	Accurate and successful in predicting overnight frost over a long period	Crop Management (Planting time decision)
	Image-based AI management system for wheat	Li <i>et al.</i> (2002)	ANN (BPNN)	Uses pixel labelling algorithms for image strengthening	Fertilizer application time decision
	Soybean crop management system	Prakash <i>et al.</i> (2013)	Fuzzy logic	More accurate predictions compared to available crop modelling packages	Crop Management (Planting time decision)
	Soil moisture monitoring system	Athani <i>et al.</i> (2017)	IoT-enabled arduino sensors	Vastly decreases the manufacturing and maintenance costs	Reduction of COP
	Paddy irrigation management system	Arif <i>et al.</i> (2013)	ANN	Uses inputs of reference evapotranspiration and precipitation	Water management
	Paddy land levelling system	Si <i>et al.</i> (2007)	Fuzzy logic	Fuzzy system in the controller judges the land level	Land Preparation
	Stem water potential estimator	Valdes-Vela <i>et al.</i> (2015)	Fuzzy logic	Greater approximation power compared to other models	Water management
	Contaminated soil classificatory tool	Lopez <i>et al.</i> (2008)	Fuzzy logic	Greater accuracy over typical computer-based models	Land and crop selection
	Soybean aphid control system	Peixoto <i>et al.</i> (2007)	Fuzzy logic	Predict the timing and release of predators for the biological control	Pest management
	“TEAPEST®”	Ghosh I. and Samanta, (2003)	Fuzzy logic	Address the issue of lack of human expertise	Pest Management
	Olive pest control system	Jesus, (2008)	Fuzzy logic	Combined GIS with computer languages Perl and PHP	Pest management
	System for detecting mature whiteflies on rose leaves	Boissard <i>et al.</i> (2007)	ML	Reliable for rapid detection of whiteflies	Pest management
	AI assisted weed identification system	Tobal and Mokthar (2014)	ANN	Minimize the time of classification training and error	Weed control
	Weed identification system in paddy fields	Barrero <i>et al.</i> (2016)	ANN	Based on areal image analysis	Weed control
	Field weed identification system	Eddy <i>et al.</i> (2008)	ANN	Improves crop/ weed species discrimination	Weed control
	Novel weed management strategy	Perez <i>et al.</i> (2016)	ML	Combines UAVs, image processing and ML	Weed control
Expert system for diagnosis of potato diseases	Boyd and Sun (1993)	Rule-based computer program	Can diagnose eleven pathogenic diseases and six nonpathogenic diseases	Disease management	

Expert system for diagnosing diseases in rice plant	Sarma <i>et al.</i> (2010)	Rule based computer program	Based on logic programming approach	Disease management
Leaf image classification system	Sladojevic <i>et al.</i> (2016)	ANN	Uses deep convolutional networks	Disease management
System for diagnosing diseases of oilseed-crops	Kolhe <i>et al.</i> (2009)	Fuzzy logic	Much faster Inference compared to earlier models	Disease management
Detection system for <i>Rhizopusstolonifer</i> Spores on Red Tomatoes	Hahn <i>et al.</i> (2004)	ANN	Very useful as 80% of the total loss in pre-packaged tomatoes	Disease management
System for predicting the wetness on wheat flag leaves	Panda, (2020)	ANN	Uses environmental variables recorded in an electronic data logger	Disease management
System for corn and soybean yield prediction	Kaul <i>et al.</i> (2004)	ANN	Produced more accurate predictions compared to those from regression models	Yield prediction (decision making)
System for rice yield prediction	Ji <i>et al.</i> (2007)	ANN	More accurate than linear regression models for the yield predictions	Yield prediction (decision making)
System for cotton yield prediction	Zhang <i>et al.</i> (2008)	ANN	More realistic trends versus input factors and predicted yields	Yield prediction (decision making)
System for wheat yield prediction	Russ <i>et al.</i> (2008)	ANN	Uses cheaply-available in-season data.	Yield prediction (decision making)
System for jute yield prediction	Rahman and Bala (2010)	ANN	Could be used to predict production at different locations	Yield prediction (decision making)
System for greenhouse tomato yield prediction	Ehret <i>et al.</i> (2011)	ANN	An opportunity to relate real-time crop status to current environmental conditions	Yield prediction (decision making)
System for predicting the environmental impacts from watermelon production systems	Nabavi-Pelesaraei <i>et al.</i> (2016)	ANN	Able to predict the energy usage and greenhouse gas production	Sustainable agriculture
System for measuring the adaptability and phenotypic stability of genotypes in breeding programs in Common bean	Correa <i>et al.</i> (2016)	ANN	Simulated genotypes can be used to train and validate neural networks	Breeding efficiency improvement
System for evaluating phenotypic characteristics on citrus crops	Harfouche <i>et al.</i> (2019)	UAV	Provides a consistent, more direct, cost-effective, and a rapid method to evaluate phenotypic characteristics	Breeding efficiency improvement
System to accelerate the selection process and improve breeding efficiency	Hua <i>et al.</i> (2019)	ML	classify pixels of the original images and the corresponding degraded images into either vegetation or background classes	Breeding efficiency improvement
Milking	Fuentes <i>et al.</i> (2020)	ML	Automatically milking and detect the disease condition such as mastitis and	Productivity improvement, Disease management

			predict the milk yield. And it improves the milk yield through increasing milking frequency	
Meat quality assessment	Suzuki, (2011); Mittal and Zhang, (2000)	ANN	Determine meat chemical quality such as tenderness, color, marbling score, water holding capacity	Meat quality improvement
	Prevolnik <i>et al.</i> (2009)	ANN	Prediction of meat chemical properties	Meat quality improvement
	Li <i>et al.</i> (1999); Lu <i>et al.</i> (2000)	ANN	assessment of meat properties based on digital images of meat surface	Meat quality improvement
	Borggaard <i>et al.</i> (1996)	ANN	carcass quality evaluation in bovine carcasses	Meat quality improvement
Animal breeding	Gonzalez-Recio <i>et al.</i> (2011)	ML	Improve a predictive performance measure by repeated observation of experiences in genome prediction	Productivity improvement and reduction of COP
	Gonzalez-Recio <i>et al.</i> (2009); Long <i>et al.</i> (2011)	ANN, Support Vector Machines, Random Forests	For genome-enabled prediction in livestock	Productivity improvement and reduction of COP
	Gonzalez-Recio <i>et al.</i> (2014)	ML	Provide a larger and more general suite of flexible methods for genome-wide prediction	Productivity improvement and reduction of COP
	Neethirajan, (2020)	ML	predicting body weight from camera images	Decision making
	Morota <i>et al.</i> (2018)	ML	To check the phenotype quality Successful in identifying outliers in the data and applied to filter and edit data prior to genetic evaluation	Decision making
	Chandraratne <i>et al.</i> (2007)	ANN	carcass quality evaluation in lamb	Meat quality improvement
	Ellis and Goodacre, (2001)	ML	Analytical approach for spoilage identification	Meat quality improvement
	Animal health management	Kamphuis <i>et al.</i> (2008)	Fuzzy logic algorithm	Identify the mastitis in milking cow
De la fuente <i>et al.</i> (2018)		ML and Fuzzy Deformable Prototypes	Predict the correct protective antigens provided solutions in order to produce vaccines for prevention and control of tick-borne diseases	Disease management
Fuentes <i>et al.</i> (2020)		ML	Predict milk yield, fat and protein content, and actual cow concentrate feed intake	Productivity improvement

	Anderson <i>et al.</i> (2000)	ML	To produce the vaccine to prevent neosporosis	Disease management	
	O'Leary <i>et al.</i> (2020); Byabazaire <i>et al.</i> (2019)	ML	Identify lameness in cattle automatically and to isolate the animal or treat immediately to avoid any further effects of lameness	Maintaining animal welfare & hygiene	
	Neethirajan, (2020)	ML	Facial recognition to monitor the behavior of animals to maintain good health throughout the herd	Maintaining animal welfare & hygiene	
	Rizvi <i>et al.</i> (2005)	ANN	Identifying veins or any other target in robotic injection system to deliver vaccines and for automated blood sampling	Disease management	
Aquaculture production	Marzuki <i>et al.</i> (2017)	ML	Identify and remove odd – shaped fish seed from the rearing cage in the fish seed screening process to prevent the IUU fishing	Productivity improvement	
Accessibility	Food desert identifier	Zhao, (2020)	Big data analytics and ML	Locates areas with low food access	Decision making
	Food desert identifier	Amin <i>et al.</i> (2020)	ML	Detects food deserts and food swamps with a prediction accuracy of 72%	Decision making
	Decision tool to evaluate the performance of agriculture food value chain	Liu <i>et al.</i> (2019)	Fuzzy logic	Integrates TFN, AHP and TOPSIS	Decision making
	Forecasting of food production	Sharma and Patil (2015)	Fuzzy logic	Forecast the production and consumption of rice	Decision making
	Forecasting of food production	Yan <i>et al.</i> (2015)	ML	Uses ANN, SVM, GP and GPR to forecast future milk yield	Decision making
	Supply chain optimization	Cheraghalipour <i>et al.</i> (2018)	Evolutionary ML	Reduce held inventory and cost in supply chains	Efficient food distribution
	Supply chain optimization	Sethanan and Pitakaso, (2016)	Evolutionary ML	Used for transportation scheduling of seafood and milk products	Efficient food distribution
	Supply chain forecasting	Liu and Hu, (2017)	ANN	Forecast the results of perishable food transportation	Decision making
System for preparing and dispensing food	Sharma <i>et al.</i> (2020)	Robotics	Extremely useful in pandemic situations like COVID-19	Efficient food distribution	

<b>Utilization</b>	Aerial cargo delivery	Faust <i>et al.</i> (2014)	Robotics	Works in environments with static obstacles	Efficient food distribution
	Monitoring food deliveries	Markovic <i>et al.</i> (2019)	IoT	More efficient approach to the modeling of assistive technologies	Efficient food distribution
	Cassava roots storage system	Babawuro <i>et al.</i> (2015)	Fuzzy logic	Uses an intelligent temperature control technique	Postharvest quality control
	Fruit storage system	Morimoto <i>et al.</i> (1997)	Fuzzy logic and ANN	RH inside the storage house is controlled	Postharvest quality control
	Potato storage system	Gottschalk (2003)	Fuzzy logic	Highly energy efficient	Postharvest quality control
	Mechanical damage detection of fruits.	Nagata <i>et al.</i> (2006); Qin <i>et al.</i> (2011); Huang <i>et al.</i> (2013); Borras <i>et al.</i> (2011)	Hyper Spectral images and ML	Used as a tool for the automatic inspection and monitoring of internal defects of fruits and vegetables in postharvest quality control laboratories	Postharvest quality control
	Assorting of fruits and vegetables	Valdez, (2020); Sofu <i>et al.</i> (2016); Larada <i>et al.</i> (2018); Al Ohali, (2011); Przybylak <i>et al.</i> , (2020)	Computer vision and deep learning	Fast, reliable, and labor inexpensive methods	Reduce labor requirement
	Detection of insect infestations in fruits.	López-García <i>et al.</i> (2010); Blasco <i>et al.</i> (2009); Blasco <i>et al.</i> (2016); Pearson <i>et al.</i> (2001)	ML	Used in combination with visible light sensors	Postharvest quality control
	Detection of hidden internal damage in fruits.	Adedeji <i>et al.</i> (2020); Rady <i>et al.</i> (2017); Liu <i>et al.</i> (2016); Ma <i>et al.</i> (2014)	Hyper Spectral Imaging and ML	Can be used without sample destruction	Postharvest quality control
	Automated food processing	Iqbal <i>et al.</i> (2017)	Robotics	Reduces the labor requirement	Reduce labor requirement
	Automated food drying	Chen and Martynenko, (2013); Barzegar <i>et al.</i> (2015); Shahabi <i>et al.</i> (2014); Nadian <i>et al.</i> (2016); Gao <i>et al.</i> (2017)	Computer vision	Fast, reliable, and nondestructive methods to automate the drying process	Food preservation
	Real-time aroma monitoring system.	Raghavan <i>et al.</i> (2010)	Fuzzy logic	Used to control microwave drying process	Food preservation

	Pomegranate grading model	Fashi <i>et al.</i> (2020)	ANFIS, ANN and RSM	Grade pomegranates based on pH	Food preservation
	Fruit classification system for bananas	Larada <i>et al.</i> (2018)	ML	Have achieved 97% accuracy	Postharvest quality control
Stability	Water resource management	Sadeghfam <i>et al.</i> (2019) Hani <i>et al.</i> (2006)	ANN	Minimize the ground water overexploitation and groundwater remediation through pump-treat-inject technology	Increasing water availability
		Hani <i>et al.</i> (2006)	ANN	Identify the reasons for spring flow decrease	Increasing water availability
		Lin <i>et al.</i> (2018)	ML	For scarcity pattern identification and efficient water abundance for equitable multi-scale water resource management	Yield prediction (decision making)
	Supply chain quality data integration method	Wang, (2019)	AI integration method of block chain technology	Supply chain of agricultural products was set up based on to cut down the additional cost	Reduction of COP
	Plant breeding	Parmley <i>et al.</i> (2019)	ML	Season seed yield prediction and prescriptive cultivar development for targeted agro-management practices	Yield prediction (decision making)
		Singh <i>et al.</i> (2016)	ML	Identification, classification, quantification and prediction of crops for effective breeding	Production improvement
	Climatic prediction	Huntingford <i>et al.</i> , (2019)	ML	To understand the full climate system that has not occurred with the direct equation analysis or visualization of measurements	Yield prediction and disease management

AI = Artificial intelligence; ANN = Artificial neural networks; ANFIS = Adaptive neuro-fuzzy inference system; BPNN = Back-propagation neural network; IoT = Internet of things; ML = Machine learning; RMS = Response surface methodology; UAV = Unmanned aerial vehicle

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