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Data Driven Farm Mechanization using Artificial Intelligence: A Review

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ABSTRACT: The farm power availability at present scenario is 2.5 kW ha^{-1} and it is predicted to be higher in upcoming years. Several attempts were made to bridge the gap between farmers and machinery utilization, to increasing efficiency and reducing drudgery to the farmers, but it cannot be achieved completely and still the gap is more and widening. The lack of skilled labors and shortage of agricultural workers are the serious problem faced by the farmers in this era of agriculture. The various inventions of farm machineries and processing industries led the way of food production for our population. But in many cases the farmers are facing a lot of unpredictable factors and losing their interest in farming. In this scenario, the idea of artificial intelligence is that, machines can readily imitate human intellect and carry out tasks ranging from the most basic to the most complex, will able to sort out all those gaps. The major aims of AI are learning, predicting, and decision making. In agriculture sector the use of artificial intelligence (AI) is to enhance a diverse range of agricultural operations to make sustainable food supply chain. These responsibilities consist of crop production, pest management, monitoring of soil and growth conditions, data organization for farmers, and workload assistance. With the help of systematic data collection and understanding the functionality of farming operations, the AI helps to increase the adoption rate of mechanization. Despite the numerous benefits, the adoption of AI in farm mechanization is not without challenges. Issues such as high initial investment costs, technical complexity, and the need for robust data infrastructure pose significant barriers to widespread implementation. Additionally, there are concerns regarding data privacy, cybersecurity, and the displacement of the agricultural workforce. To overcome these challenges, it is essential to foster collaboration between stakeholders, including farmers, researchers, technology developers, and policymakers. Investing in training and capacity-building programs can equip farmers with the necessary skills to leverage AI technologies effectively. Furthermore, developing affordable and scalable AI solutions tailored to the specific needs of smallholder farmers can accelerate the adoption of AI-driven mechanization.

Keywords: Artificial Intelligence, Machine Learning, Data Science, Agriculture, Farm Machinery.

INTRODUCTION

The use of artificial intelligence (AI) in agricultural mechanization has given rise to various technologies and applications that aid farmers in achieving more precision to control over their farming operations (Basso and Antle 2020). These technologies and software provide assistance to farmers in a number of activities, such as control of pests, application of fertilizer, rotation of crops, perfect planting of seedlings, irrigation management and timely harvesting of crops (Hamilton *et al.,* 2022). By integrating machine learning algorithms, satellite/drone imagery, temperature data, precipitation, wind speed, solar radiation with artificial intelligence (AI)-enabled technologies perform various tasks such as weather forecasting, crop sustainability evaluation, farm inspection pertaining to pests, diseases and undernourished plants (Wang *et al.,* 2019). Currently, farmers may reap the benefits of artificial intelligence by using a smart phone that supports SMS and the Sowing App, even if they do not have access to the internet. On the other hand, farmers who have access to Wi-Fi may employ AI apps to get a customized plan for their crops on a constant basis (Sarker *et al.,* 2019). Through the utilization of App solutions that are driven by the Internet of Things with artificial intelligence, farmers will not only be able to increase their revenue, and also reduce their impact on the environment, and provide food all over the world. Farmers will become agricultural scientists in the future with the assistance of artificial intelligence. Agricultural Robots that use artificial intelligence (AI) to perform a range of tasks well in agricultural environments. For example: Special robot has been specifically programmed for controlling the weeds. The robots are programmed to spot weeds and conduct quality inspections of crops throughout the sorting and eradicating processes. The problems that agriculture faces like labour forces may likewise be addressed by this kind of robots. On other hand, the biggest problems for farmers is pests, which may ruin the crops. Artificial intelligence systems enable farmers to combat pests by analyzing satellite images, comparing them with historical data, detecting their presence and type of landed insects (e.g., grasshoppers, locusts, etc.). These systems then notify farmers through smartphone alerts, allowing them to take necessary precautions and apply pest control as needed.

Big Data Technologies. IoT devices and sensors play a crucial role in data collection by monitoring various parameters like soil moisture, temperature, and crop health in real-time. These devices provide continuous and precise data, enabling farmers to make timely and informed decisions (Wolfert *et al.,* 2017). Cloud platforms are essential for storing and processing the vast amounts of data generated by IoT devices and other sources. They offer scalable storage solutions and computational power necessary for big data analytics (Sundmaeker *et al.,* 2016). Big data analytics enables real-time monitoring of crop health and early detection of diseases. By analyzing historical and current data, predictive models can forecast disease outbreaks, allowing farmers to take preventive measures (Fang *et al.,* 2019). Big data helps in optimizing the agricultural supply chain by providing insights into market trends, demand forecasting, and logistics management. This ensures efficient distribution of agricultural products, reducing losses and improving profitability (Kamble *et al.,* 2020). The useful information to support data-driven decision-making for satisfying the applicable food production and supply. Through analysis of vast amounts of data from many criteria that may be combined with information about agriculture from other sources. The integrated farm models, crop growth models, water balance models, soil nutrition models, farm optimization models, and risk assessment models are generated as decision models.

Machine Learning in Agriculture. Machine learning (ML), which has emerged along with the availability of vast quantities of data and high-performance computers, has generated new potential for the understanding, quantification, and decipherment of data-intensive processes in agricultural operational settings (Van Loon *et al.,* 2020). The notion that machine learning (ML) is the domain of computer science that empowers computers to acquire new knowledge autonomously, without requiring human guidance, is a widely held belief. This is a common understanding of machine learning. Supervised learning and unsupervised learning are the two fundamental types of machine learning tasks. The learning signal that the system utilizes to identify these two types of learning is what defines them. By providing data with sample inputs and associated outcomes, supervised learning aims to construct a general rule that maps inputs to outputs. In a constantly changing environment, it is not uncommon for certain inputs to be partly accessible while some of the desired outputs are either absent or provided just as feedback for the actions taken (reinforcement learning). When labels are missing from test data, the trained model use its knowledge to fill in the gaps in a supervised setting. Unsupervised learning, on the other hand, uses unlabeled data without dividing it into training and test sets. The learner looks at incoming data to uncover hidden patterns.

Data Transmission. In order to increase crop yields and quality with less human effort, the agricultural sector will greatly benefit from the ultra-fast generation network. Farmers may increase their knowledge and output with the help of smart and precision farming. The arrival of 5G will bring about considerable changes to the agricultural and farming-related industries. The 5G network provides cloud computing services that are founded on the internet of things (IoT) and provide adaptable and efficient solutions for intelligent farming. Over time, this will enable unmanned farms to carry out the planting, ploughing, and management phases of agricultural production with little to no assistance from humans. The equipment for this procedure will be energy-efficient, environmentally responsible, safe, and trustworthy. This is because 5G has more bandwidth than 4G, it can also link billions of devices. In terms of uploading and downloading speeds, 5G will be up to 100 times faster than the present 4G and 4G LTE standards. This indicates that a two-hour movie would download in less than four seconds over 5G, compared to six minutes on 4G. The ITU is responsible for creating the technical standards for 5G (IMT-2020). Uplink peak data rates per mobile station are 10 GBPS, while downlink peak data rates are 20 GBPS.

Precision Agriculture with Automation. Drones, UAVs, and UGVs will able to work together to build a smart integrated system that can automatically spray nutrients and inputs into crops, receive photographs of crop health in real time for analysis and insights. Crop productivity and agricultural efficiency are increased by using this application in farming. The machine vision for smart farming device automation and guiding can be combined with tractors. The independent robots deployed for the tasks like harvesting, planting, weeding, etc. It assists in separating the best crop produce from the worst harvests, determining which produce are stable for longer logistics, and determining produce crops that can be sold locally which has less shelf life. Artificial Intelligence have the capability to gather and analyze vast quantities of data from public and government sources in order to resolve a variety of confusing matters by utilizing machine learning. Additionally, it improves water assessment and availability, which boosts agricultural yields. Artificial intelligence is going to make farming more of hybrid, and biological expertise in future. This will benefit farmers in many ways, including reduced post-harvest losses and increased productivity. According to United Nations Estimates, two-thirds of the global population will reside in urban areas by 2050; thus, farmers will be obligated to decrease their labour intensity. The use of artificial intelligence in the agricultural sector holds promise for the automation of diverse procedures, mitigation of risks, and provision of farmers with better farming experience characterized by increased efficiency (Panpatte, 2018). An analogous evaluation was conducted to assess the efficacy of support vector machines (SVM) and artificial neural networks (ANN) in weed identification with a help of moment-invariant shape data and Fourier descriptors. According to the data, SVM produced a greater accuracy of 96.67 percent for weeds and sugar beets, whereas ANN produced a lesser accuracy of 93.33 percent (Bakhshipour and Jafari 2018). Using the Haar wavelet filter's textural properties, artificial neural networks can distinguish between sugar beets and weeds. By including textural data into the ANN architecture, the findings showed an accuracy of 89.3% for sugar beets and 88.0 % for weeds (Bakhshipour *et al.,* 2017). Using a fuzzy classifier, a robotic model for weed detection in sugarcane fields was developed. With the help of this algorithm, which extracts textural features and weed identification accuracy was found 92.9 percent (Sujaritha *et al.,* 2017). A strategy for optimizing the robot and its workspace (the tree design) simultaneously created and tested for various training methods. The robot system design optimization was mainly emphasized, and the best training method was determined by minimizing robot's overall time (Bloch *et al.,* 2018). In order to distinguish between weeds in maize fields, a combination of the SVM and carefully chosen colour characteristics was used. Over the course of three years of testing, it was found that the chosen colour indices maintained consistent accuracy of 90.19%, 92.36%, and 93.87% regardless of the weather (Zheng *et al.,* 2017). Spectral data that may be used to distinguish wheat from other winter grasses and broadleaf weeds. A total accuracy of 85% was shown using a four class discriminating model, which included broadleaf, grasses, soil, and wheat (Herrmann *et al.,* 2013). Through the use of different sensors such as temperature, humidity, and soil moisture, it would be able to identify illnesses in huge fields of crops at an early stage and then make recommendations about the use of fertilizers. A training and test dataset may be created using the aforementioned technique. When the testing phase is over, it will look for photos in the trained dataset that match the ones in the test samples. The next step is to remove the illness photos in the pre-processing stage. The pre-processing step employs a k-means clustering technique to split the picture into a substantial number of parts. Following this, Support Vector Machine (SVM) classifiers are implemented to classify each component. The genetic algorithm is used for edge identification, which yields good results. Monitoring, detection, and service quality are the three aims of this dissertation to be assessed in the suggested system (Zheng *et al.,* 2017). The Single Shot MultiBox Detector (SSD) architecture is the foundation of the YOLOv2 algorithm, which offers a quicker recognition rate while maintaining an accuracy level that is equivalent of the SSD500 method. Using the VOC 2007 dataset, its maximum achievable precision (mAP) is 76.6 percent and its maximum recognition speed is 67 fs^{-1}. With its 19 convolutional layers and 5 maximum pool layers, YOLOv2 improves upon the YOLO's detection speed while increasing its accuracy, according to the Darknet-19 network model. Using the VOC 2007 dataset, the YOLOv2 model outperforms Faster ReCNN in terms of detection accuracy and can reach a speed of 40 fs^{-1} with images having a resolution of 544 * 544 pixels (Redmon and Farhadi 2016). In detection algorithm, the field photos were analyzed for spectral reflectance to identify six different types of weeds, in soybean plants. With an overall accuracy of 84%, the optimal spectral band combination (BSBC) outperformed all three methodologies, such as principal component analysis (PCA), linear discriminant analysis (LDA), and three-year datasets. The fruit number counting approach was used to capture images of mangoes that were shot at night using artificial illumination. Practicality concerns may arise about the approach owing to the need of using lighting equipment during daylight imaging as a consequence of the artificial illumination system (Qureshi, 2016). By using the multi-viewpoint technique, the mango occlusion issue was resolved. The tracking and localization of fruits was accomplished by analyzing the picture sequences from various perspectives. Unfortunately, this method's real-time performance was subpar, and it required complex auxiliary equipment (Herrmann *et al.,* 2013). One such design is MangoNet, which uses deep convolutional neural networks (CNNs) to identify mangoes by semantic segmentation. It outperformed various topologies of fully convolutional networks (FCNs), according to the various trials (Kestur *et al.*, 2019). Using smart sensing of airbag inflators, an autonomously deployable front-mounted rollover protection system (ROPS) for narrow tractors was designed and tested. This system allowed for the simultaneous expansion of the ROPS's top breadth and height. As a result of the twofold modification of the ROPS geometry, it is possible to reduce the height of the ROPS, bending moments at critical sections, and the sections of the ROPS beams. Additionally, the continuous rolling risk is reduced, and safety zone is expanded laterally (Ballesteros *et al*., 2015). The purpose of an electronic system that is intended to monitor the stability of a tractor on sloped terrain is to provide the operator with a series of warnings as the risk of instability and rollover. A variety of tractor types are compatible with the IncliSafe device, which is available for purchase as an aftermarket addition (Dtaebt, 2015).

Prediction Algorithms in Mechanization. A fuzzy control technique, in which the ideal steer angles for a steering controller are determined using posture information. This approach considers errors related to location and orientation. The purpose of constructing kinematic modelling of a differential-drive vehicle was to simulate and evaluate the durability of the controller. Tracking performance was determined to be significant after implementation of this technique (Kumar *et al.,* 2012). An application designed specifically for smartphones and used to transmit data from the accelerometer as well as gyroscope sensors that are incorporated in smartphone to a computer via the usage of a wireless network. The Safe Driving app demonstrated the feasibility of using a mobile phone to gather data for a tractor's stability evaluation while it is in motion. These programmes show the operator potential danger spots and how to stay out of harm's way (Liu and Koc 2015). Using a cascaded estimator technique, the impact of hitch point loading on tractor dynamics was examined. The experimental findings demonstrate that the capability to adjust the controller gain for consistent yaw dynamic control of the tractor is provided by the online estimate of system changes (Gartley and Bevly 2008). A controller that tracks trajectories and simulates autonomous vehicle path-following systems using sliding mode control showed promising results when tested with a high beginning position inaccuracy (Solea and Nunes 2007). The steering controller architecture was enhanced with a new path-tracking algorithm that improves tracking performance by minimizing transient overshoots at curve beginnings and ends. The system is based on estimating sliding parameters like slip and steering angle (Lenain *et al.,* 2006). To avoid collisions while working together, a master robot and a slave robot, which use a wireless local area network to broadcast the slave robot's GPS location to the master robot. Two robot tractors could be safely avoided from colliding by using the safety technique, but it was unable to detect anything else (Noguchi *et al.,* 2004). The results indicated that the use of a dynamic route search technique in tractor resulted a moderate improvement in path tracking, with a lateral variation of less than 0.1 metre, while the tractor followed straight or slightly curved tracks at speeds of up to 3.5 metres per second. More precise assessment of slippage on curved pathways is necessary, nevertheless and since accuracy decreased when going on such paths, particularly in very abrupt bends (Zhang and Qiu 2004). In order to test the autonomous harvesting of a field that was opened up by a human operator, an automated self-propelled windrower system was developed. This system used either an inertial sensor combined with a differential global positioning system (DGPS) or a camera. Two cameras are mounted on the side of the cab of an autonomously driven windrower. When shadow correction was complete, the difference in reflectance was used to find the boundaries between the parts that had been cut and those that had not been cut. It was also found that there were obstacles at the very end of the crop row, where there was no longer any edge (based on their different colour). The position was determined by using additional sensors in conjunction with the data from the 5 Hz DGPS. A speed range of 1.5–2.0 metres per second is achievable for the system. The inaccuracy of the DGPS varied from 40 to 60 millimetres, but the error determined by eyesight was between 50 and 300 millimetres (Pilarski *et al.,* 2002). Using the leakage percentage of the fast Fourier transform, it was able to differentiate between fruit and background objects in digital photographs that were taken outdoors in natural colour. In the sixty images that was used for validation, eighty-two percent of the vegetables and fruits were properly identified (Bansal *et al*., 2011). It is necessary to create two artificial neural network (ANN) models in order to predict the amount of moisture present in paddy fields, which had a much lower amount of meteorological data. Following the examination of both observed and forecasted soil moisture levels, both models were followed by confirmation and verification. Initially, the ANN model was constructed in order to estimate ET. The air temperature's lowest, average, and maximum readings were utilized. The second model was created using data on air temperature, precipitation, and solar radiation. With minimum use of time, effort, and weather data, both of these algorithms were able to reliably estimate soil moisture in rice fields (Arif *et al.,* 2012). Soil compaction could be diminished by using a decision support system that plans routes for agricultural vehicles with time-dependent loads. Furthermore, the investigation in which soil compaction causes higher energy demands, higher CO^2 emissions, and worse yields (Bochtis *et al.,* 2012). Similarly, the detected HLBs using two sets of aerial multispectral and hyperspectral pictures. Several techniques were implemented, including mixture tuned matched filtering (MTMF), spectral angle mapping (SAM), and linear spectral un-mixing. It was achieved an 87% detection accuracy with multispectral photos and 80% accuracy with hyperspectral images for the test locations. Possible erroneous ground truthing was a major cause of inaccuracy in the sample coordinates. Results were better with MTMF than with SAM. A range of vegetation indicators were used to mitigate the occurrence of false positives. These indicators included the anthocyanin reflectance index, the carotenoid reflectance index (CRI), and the air resistance vegetation index (ARVI) (Kumar *et al.,* 2012). A computer vision system that is able to identify rows of growing crops. It was composed of two distinct subsystems: a processing subsystem that was both slow and accurate, and a processing subsystem that was both speedy and accurate, producing results quickly (robust crop row detection). Through the use of this method in a variety of contexts, an average of eighty percent of the crops were accurately identified. According to (Burgos-Artizzu *et al.,* 2011) a machine vision system that makes use of a one-of-a-kind algorithm called "Parse and Add" with number of different stages of photo processing. A debris mass map was created from the field experiment photographs. With this map, could be pinpoint the main causes of debris and identifying the positioning of fruits for future harvests with less mess (Bansal *et al.,* 2011). The idea of chained systems is used to construct the cornering and sliding mode controllers. Based on the information that was broadcast, the suggested observer and controller demonstrated remarkable resilience against time-varying lateral disturbances and incorrect side-slip angles (Fang *et al.,* 2011). An algorithm for path-tracking that is appropriate for controlling the headland turning of a farm tractor was developed via a simulation research that used a neural network and the pure pursuit approach. Finding the best way for an agricultural equipment to change heads-of-field was shown to be viable using the pure pursuit strategy in the simulation results. Nevertheless, the method for optimising the algorithm's parameters in order to achieve headland turning in simulation was left out (Burgos-Artizzu *et al.,* 2011). For the purpose of identifying the early crop rows, a method called least squares was implemented. By use of categorising the feature points that were obtained as the centres of the crop rows and clusters were successfully formed. It was ascertained that the crop line could be generated by implementation of the least squares method to suit the feature points. The sensitivity of the least squares approach to weed noise is a factor that is responsible for the reduction in crop line detection accuracy (Si *et al.,* 2010).

Agricultural Machinery Hiring System. AMHS system is aimed to provide bridge between the mechanization and the farmers. It also acts as a Farm Machinery Rental Fleet Business. It acquires a group of tractors, implements, harvesters etc., and hired drivers with the specific region using the Internet of Things preinstalled in the machinery. Customers or farmers can use the AMHS system to pre book the machineries are made available for them at their preferred location and time through web portal and smartphones. In this digital technological era it's a great chance in online industry to move whole commercial business into an app-based integration. Hereby, AMHS works as a mediator between the customers and Agricultural Machinery owners. AMHS connects operators, owners and farmers via a mobile application through GPS and the authorized agreement, privacy terms provided in software and well as security management. This enhanced precision streamline of machinery management, minimizes energy requirements for cultivation practices. In the rush to mechanize farm operations, contracting is the only useful way to familiarize, quality mechanization to small and marginal farmers. By acquiring data from different sensors, GPS, IMUs which allows the machine learning algorithm to process and predicts the cost of operation on that particular region. Thus minimizes the excessing costing and helps farmers to save their time and money. The data acquisition and analysis gives a positive connection between the societal value construction and economic output, also it depicts the application and web based model can have better on marketing potential. This AMHS creates the better farm mechanization opportunities to small /marginal farmers and uplifting their lives.

CONCLUSIONS

The integration of Artificial Intelligence (AI) in farm mechanization represents a transformative shift in modern agriculture, offering unprecedented opportunities for enhancing productivity, efficiency, and sustainability. This review has comprehensively examined the various AI-driven technologies and methodologies being employed in farm mechanization, highlighting their impact on different agricultural operations. AI technologies, such as machine learning, computer vision, and robotics, are revolutionizing traditional farming practices by enabling precise and efficient field operations. The application of AI in machinery, such as autonomous tractors, drones, and harvesters, has demonstrated significant improvements in field productivity and resource management. These smart machines are capable of performing tasks with high precision, reducing human labor and minimizing input wastage, thus contributing to cost savings and environmental conservation. The use of AI in predictive analytics and decision support systems has shown great promise in enhancing farm management strategies. By leveraging large datasets and sophisticated algorithms, farmers can make informed decisions regarding crop selection, planting schedules, irrigation, and pest control. This data-driven approach not only optimizes resource utilization but also mitigates risks associated with climate variability and market fluctuations. Moreover, AI-driven mechanization facilitates real-time monitoring and management of farm operations. Through the deployment of IoT devices and sensors, farmers can continuously monitor soil health, crop growth, and machinery performance. This real-time data collection and analysis enable timely interventions, ensuring optimal growing conditions and reducing the likelihood of crop failure. In conclusion, the integration of AI in farm mechanization holds immense potential to revolutionize agriculture, making it more efficient, sustainable, and resilient. While challenges remain, continued advancements in AI technologies, combined with supportive policies and collaborative efforts, can pave the way for a data-driven agricultural future. By embracing AI, the farming community can achieve higher productivity, better resource management, and improved economic outcomes, ultimately contributing to global food security and sustainable development.

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