MAIN DIRECTIONS OF APPLICATION OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE: A REVIEW

PRINCIPALELE DIRECȚII DE APLICARE A INTELIGENȚEI ARTIFICIALE ÎN AGRICULTURĂ: O RECENZIE

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ABSTRACT
The implementation of artificial intelligence (AI) techniques and tools in all agricultural sectors can ensure the transformation of agriculture into a smarter, more efficient and more sustainable sector, ready to face the challenges of the future. The paper provides a review of recent applications of AI, focused on crop monitoring, precision agriculture, robotics, animal management and supply chain optimization, with examples of research, studies and applications carried out in this regard in the last 5 years. The general conclusion is that, in the current conditions of the need to develop the agricultural sector on a sustainable basis and for economic efficiency, the use of emerging technologies (AI) and their implementation in all activities and processes related to agriculture must be accelerated.

ABSTRACT
Implementarea tehnicilor și instrumentelor de inteligență artificială (IA) în toate sectoarele agricole poate asigura transformarea agriculturii într-un sector mai inteligent, mai eficient și mai sustenabil, pregătit să facă față provocărilor viitorului. Lucrarea oferă o trecere în revistă a aplicațiilor recente ale IA, axate pe monitorizarea culturilor, agricultura de precizie, robotică, managementul animalelor și optimizarea lanțului de aprovizionare, cu exemple de cercetări, studii și aplicații efectuate în acest sens în ultimii 5 ani. Concluzia generală este că, în condițiile actuale ale necesității dezvoltării sectorului agricol pe baze sustenabile și pentru eficiență economică, trebuie accelerata utilizarea tehnologiilor emergente (AI) și implementarea acestora în toate activitățile și procesele legate de agricultură.

INTRODUCTION
The challenges of the future through the development and implementation of AI in contemporary human society also involve agriculture, agriculture being (if not the most important then) one of the most important industries. The need for agriculture to be able to provide the necessary food for humanity, which is in continuous growth, together with maintaining high standards in terms of sustainability of agricultural technologies and processes, leads to the adoption of solutions that increase the efficiency of this industry. This is where AI tools and techniques come into play, which together with the increase in the degree of computerization of agriculture, manage through their implementation to transform agriculture into a smarter, more efficient and more sustainable sector, ready to face the challenges of the future (*Sharma et al., 2022*; *Elbasi et al., 2024*). Thus, it can be said that the need for studies and research carried out in this direction will revolutionize agriculture, offering advanced solutions to face contemporary challenges, from global population growth to climate change.

The directions of application of AI in the agricultural industry are numerous (due to the complex nature of agriculture), from the use of robots and autonomous systems to market analysis, financing and insurance of agricultural farms, and from the point of view of the most important directions of application of AI (which will be discussed further in this article), they are presented in Figure 1.

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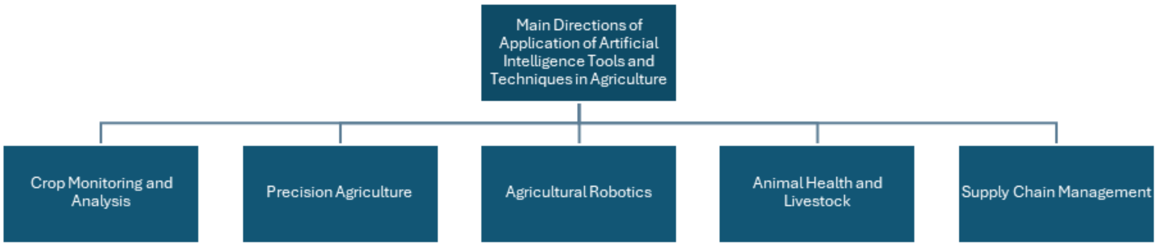

Fig. 1 - Main directions of application of artificial intelligence in agriculture

The interconnections between these technologies allow for data-driven decision-making and automation in smart farm management (Fig. 2). Figure 2 shows a flow chart of how advanced machine learning techniques are integrated into modern agricultural management systems. Deep Learning (DL), Reinforcement Learning (RL), and Natural Language Processing (NLP) are fundamental technologies because they feed into a centralized machine learning (ML) environment, which serves as the main processing centre where models are trained, refined, and applied. It then dynamically interacts with datasets that provide the raw information needed for learning and also receives feedback from the machine learning environment to improve future predictions and decisions. Based on the datasets, agricultural management (the practical application layer) is performed, by taking the information from the data and AI models and applying them to real-world agricultural operations. AI-based agricultural management can be considered a decision support system that synthesizes all this information to help farmers make informed, data-driven choices.

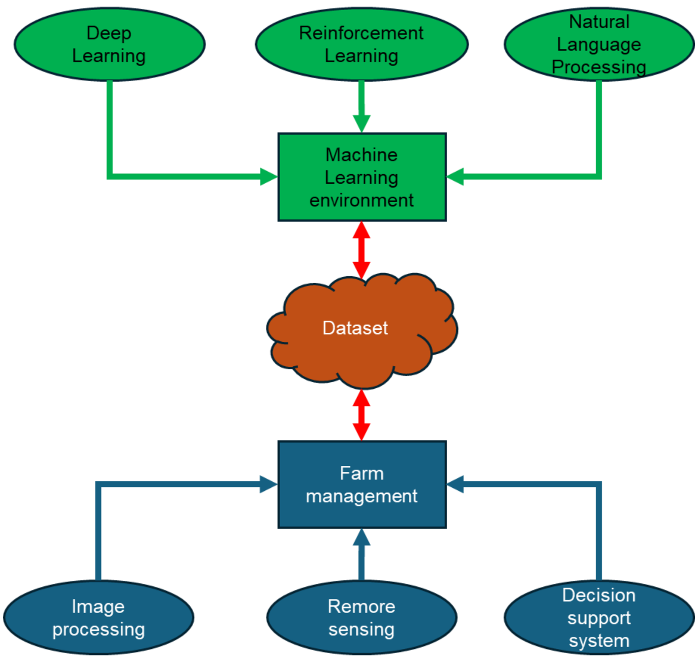

Fig. 2 - AI techniques applicable to intelligent farm management (adapted from *Wei et al., 2024*)

The application of artificial intelligence models and tools in agriculture presents a number of challenges, one of which is the large initial investment required to implement AI technologies, including the price of sensors and specialized hardware and software (which can be prohibitive for small and medium-sized farms). Additionally, problems with easy and continuous internet connectivity are common in rural areas, making it difficult to collect and send data in real time, which can affect the effectiveness of artificial intelligence systems that depend on continuous data acquisition, storage, and analysis.

Technical complexity and skills shortages are another major obstacle, as many farmers may not have the technical knowledge to run and maintain AI systems. This can make people reluctant to adopt new technologies, especially those who are more accustomed to conventional farming practices. In addition, there are concerns about the ownership and confidentiality of production data. The broad applicability of AI models can also be limited by the variability of agricultural environments. This is because different regions have different soil types, weather patterns, and crop varieties, making it difficult to create AI solutions that work everywhere. Technology developers, policymakers, and the farming community must work together to overcome these obstacles and ensure that AI solutions are available, affordable, tailored to farmers' needs, and provide effective and sustainable solutions. In order to increase the level of knowledge of the application potential of AI tools and technologies in agriculture, this paper, in the form of a review, aims to present the most current research conducted (the last 5 years) and the results obtained in the application of AI in several areas of interest in the agricultural sector.

CROP MONITORING AND ANALYSIS

Crop monitoring and analysis focuses on collecting and interpreting data on plant health and development, enabling rapid and informed interventions by farmers to increase agricultural production (*Chiu et. al., 2020; Ipate et al., 2024*). The main AI technologies and tools for development and application are the use of drones and remote sensing technologies, computer vision and pattern recognition, and predictive data analysis (Fig. 3).

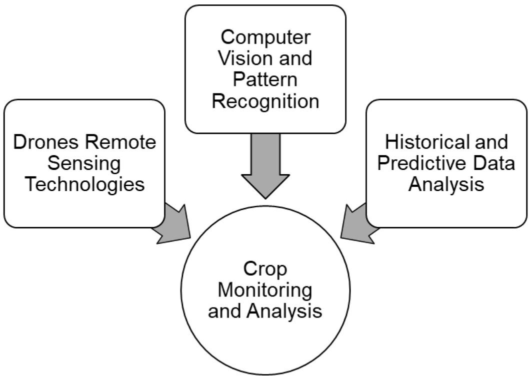

Fig. 3 - Applications of artificial intelligence in crop monitoring and analysis

Drones equipped with advanced sensors (multispectral, hyperspectral, thermal) fly over fields and collect massive amounts of data (*Milas, 2018; Zhang and Zhu, 2023*). This data includes information about leaf health (principally by considering the vegetation index - NDVI), soil moisture level, the presence of water or nutritional stress and early detection of pests and diseases. There are already developed and applied AI algorithms that analyse this captured data to create variability maps, indicating areas that require attention, and the workflow of using a ML application is presented in Figure 4.

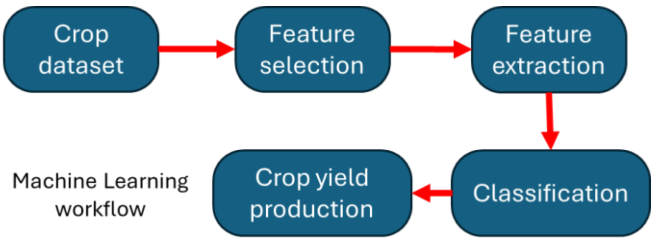

Fig. 4 - Workflow of an ML application in crop yield production prediction (adapted from *Gupta et al., 2022*)

The use of computer vision and pattern recognition is achieved through high-resolution cameras mounted on agricultural machinery and/or autonomous vehicles or even directly on plants, which capture detailed images in real time. Furthermore, computer vision systems, powered by AI, can accurately identify crop weeds (type and density), count plants, assess crop maturity, and detect early signs of disease or insect infestation (*Patrício and Rieder, 2018*). This information allows farmers to make informed decisions regarding the application of specific treatments and reduce/eliminate potential production losses. *Cheng et al. (2025)* developed a method for detecting adult peach moths based on an AI model YOLOv8m to address the difficult problem of detecting peach moths. The accuracy of the improved model increased by 3.4% compared to YOLOv8m. The recall improved by 2.1%, and the mAP parameter improved by 1.2%. The proposed solution shows an improvement in the effectiveness of the model in detecting adult peach moths, and the results provide solid technical support for the subsequent real-time monitoring of peach moths.

In response to the recommendations of the *Food and Agriculture Organization of the United Nations (2014)* and the *Committee on Agriculture and Rural Development of the European Parliament (2009)* regarding the sustainable development of agriculture, current research efforts focus on increasing crop yields and reducing pesticide consumption by prioritizing non-chemical methods (agrotechnical, physical, biological, etc.) and applying pesticides only when strictly necessary, using appropriate monitoring tools (warning, forecasting, and early diagnosis). AI models employed for crop monitoring are generally structured into three functional modules: data collection, intelligent data processing through AI models, and generation of actionable recommendations for crop management (Fig. 5).

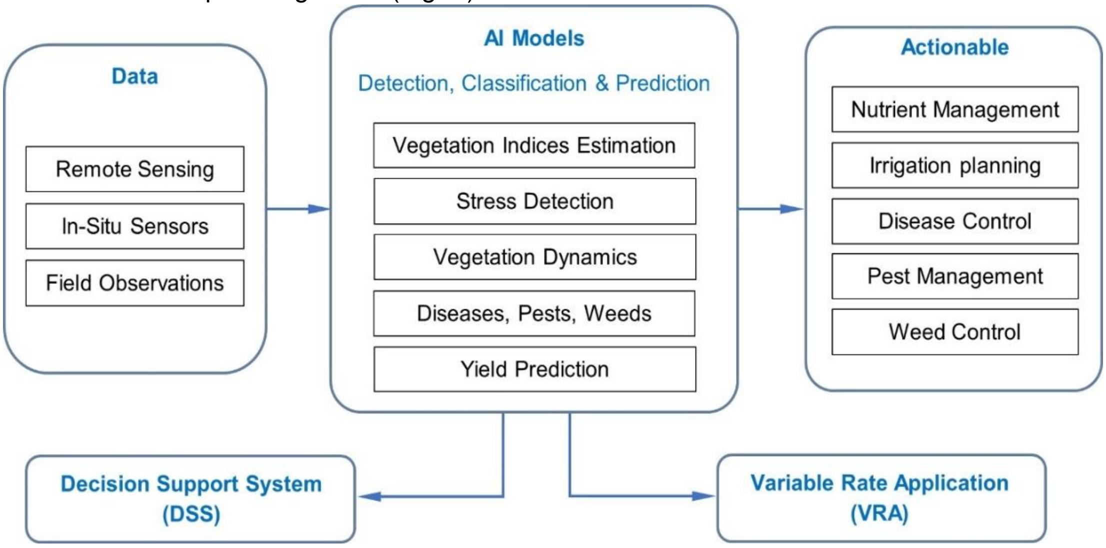

Fig. 5 – AI workflow model for culture monitoring

AI based models integrate heterogeneous primary inputs obtained from complementary information sources, including RGB, multispectral, and hyperspectral imagery, data captured by drones, unmanned aerial vehicles (UAV), or fixed cameras; real-time measurements provided by in-situ sensors (microclimate, humidity, soil parameters, insect population density, etc.); as well as direct field observations conducted by operators or farmers. The quality and diversity of visual data, affected by species differences, illumination conditions, background complexity, and disease development stages, are critical factors in developing robust and generalizable AI models for agricultural applications. Significant accuracy variations (ranging from 60% to 100%) have been reported depending on image dataset diversity in terms of species, lighting conditions, and background variability (*Barbedo, 2018*). *De Silva and Brown (2023)* reported improved disease detection accuracy in apple crops (exceeding 98%) using multispectral imagery acquired from multiple locations, demonstrating that both additional spectral features and contextual variability (location, illumination) substantially enhance model performance. Furthermore, the deployment of multispectral and hyperspectral sensors—capable of capturing information in spectral bands invisible to the human eye (e.g., Near-Infrared NIR and Red Edge)—facilitates early stress detection and improves the generalization capability of CNN (*Zandi et al., 2025*).

The AI processing module employs machine learning and DL algorithms based on convolutional neural networks (CNN) for the identification and prediction of biotic stress factors (diseases, pests, and weeds). CNN architectures used for the acquisition and processing of agricultural images, encompassing registration, classification, detection, and segmentation stages (Fig. 6), provide high levels of accuracy and precision in detection, prediction, and the generation of recommendations for Integrated Pest Management (IPM) applications. Current research highlights multiple opportunities to enhance AI model performance through the implementation of optimized and task-specific CNN architectures tailored to each stage of the image processing workflow.

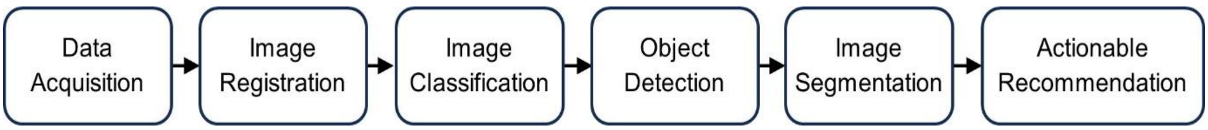

Fig. 6 – Sequence of agricultural image processing stages

Image registration (the geometric alignment of images acquired from different sources such as drones, satellites, and multispectral or hyperspectral cameras) ensures both temporal and spectral data consistency. In agricultural applications, this stage is critical for temporal series comparison (e.g., monitoring water stress and disease progression), multisensory data fusion (RGB, NIR, thermal), and geometric calibration of UAV imagery with satellite orthophotos. Traditional feature-matching methods (SIFT, SURF, ORB, RANSAC) have proven effective but remain limited under varying perspective, illumination, and texture conditions (*Cocianu et al., 2023*). Conversely, convolutional neural networks provide a robust framework for registering images from heterogeneous sources. Correlation-based architectures for UAV and multispectral image registration in temporal analysis (*Rocco et al., 2017*), spatial transformer modules integrated into agricultural CNN for automatic correction of UAV flight distortions (*Reedha et al., 2022*), hybrid CNN–Transformer models combining local feature extraction with global correspondence (*Li et al., 2024*), and radiometric as well as orthorectification procedures based on GPS and DEM models (*Habib et al., 2016*) have demonstrated significant improvements in geometric and radiometric accuracy. Furthermore, the integration of learned feature-matching algorithms (SuperPoint, SuperGlue) and fine-tuning on locally collected agricultural datasets further reduces alignment errors to below 1–2 pixels (*Jiang et al., 2024; Liu et al., 2023*), providing a solid foundation for high-resolution multisensory data fusion and minimizing error propagation in subsequent processing stages.

Image classification based on CNN provides superior accuracy compared to traditional approaches relying on handcrafted feature descriptors. Models such as ResNet, DenseNet, EfficientNet, and Inception enable robust identification of plant diseases, growth stages, and species, while transfer learning applied to agricultural datasets significantly enhances model accuracy and generalization capability (*Ferentinos, 2018; Cai et al., 2023; Ali et al., 2025*). Recent studies highlight a transition toward hybrid CNN–Transformer architectures, which combine the local feature extraction strengths of CNN with the global attention mechanisms of Transformer-based models (e.g., Vision Transformer, and Swin Transformer). These architectures achieve high performance in UAV-based crop classification, particularly under conditions of atmospheric variability (*Guo et al., 2025*).

Object detection in agricultural imagery represents a key domain for the automation of crop monitoring processes, being applied in weed identification, pest detection, disease symptom recognition, and fruit inventory estimation. Recent advances in deep learning have led to the development of CNN-based architectures and advanced object detectors such as YOLO, Faster R-CNN, SSD, and RetinaNet. One-stage models such as YOLOv5–v8 and SSD are widely employed for real-time weed detection due to their high inference speed and efficient deployment on ground or UAV platforms *(Liu et al., 2024).* In contrast, two-stage detectors such as Faster R-CNN provide higher precision when identifying small or partially occluded objects, making them suitable for pest detection and subtle symptom analysis *(Li et al., 2024).* To enhance performance, recent research incorporates data augmentation, transfer learning from pre-trained backbones (ResNet, EfficientNet), multi-scale architectures (FPN, BiFPN), and attention modules for capturing contextual information *(Peng et al., 2022).* Additionally, the use of multispectral imagery and Red Edge/NIR sensors facilitates early detection of plant stress *(Darbyshire et al., 2024).* State-of-the-art models such as YOLOv8 and RetinaNet, adapted for agricultural applications, achieve detection accuracies exceeding 90% under controlled conditions; however, challenges remain under varying illumination, texture, and object density *(Popescu et al., 2023).* Overall, the combination of high-speed detectors with advanced optimization techniques enables the development of robust smart spraying, precision weeding, and automated crop health monitoring systems. Current research trends focus on lightweight models for edge deployment, multi-temporal detection, and multisensory data fusion to further improve accuracy and robustness *(Guo et al., 2023).*

Image segmentation using traditional methods based on vegetation indices (NDVI, ExG, VARI) or algorithms such as thresholding and region growing provides limited performance under conditions of spectral variability, uneven illumination, or crop–soil overlap *(Lei et al., 2023).* The evolution of DL techniques has enabled a transition toward fully convolutional network (FCN) architectures, including U-Net, SegNet, DeepLabv3+, and modern hybrid CNN–Transformer variants. Among these, U-Net and its derivatives (U-Net++, Attention U-Net) have become predominant for leaf and disease-affected area segmentation due to their ability to preserve fine spatial details *(Khan and Jung, 2024).* DeepLabv3+ and HRNet have demonstrated superior performance in weed segmentation and crop-row delineation, benefiting from the integration of dilated convolution and feature pyramid fusion modules *(Shao et al., 2025).* The integration of multispectral and hyperspectral sensors, combined with feature-level data fusion, has significantly improved segmentation accuracy under both abiotic and biotic stress conditions *(Chroni et al., 2024).* In conclusion, DL-based segmentation provides a robust foundation for the development of automated crop monitoring systems, enabling precise plant health assessment, integrated weed control, and the implementation of VRA technologies.

AI models designed for *generating quantifiable agronomic recommendations* integrate visual entities extracted from multispectral imagery, vegetation indices (NDVI, NDRE, GNDVI), and pedoclimatic information to produce actionable decisions (e.g., optimal fertilizer rates, parcel-level irrigation volumes). By correlating these variables with phenological stages, AI models can identify optimal intervention windows and estimate crop response to agricultural inputs *(Chen et al., 2025).* Hybrid architectures combining CNN with Transformer modules enable efficient fusion of visual and contextual information, generating high-precision prescription maps for precision agriculture *(Wang, 2025).* Feature-level fusion between spectral channels and meteorological parameters significantly enhances system robustness under variable illumination and climatic conditions, reducing estimation errors related to abiotic and biotic stress. Moreover, integrating time-series vegetation indices and climate data into Long Short-Term Memory (LSTM) models supports dynamic prediction of vegetative activity and yield performance *(Nieto et al., 2021).* Model validation is conducted through local calibration using experimental dose–response data and in-field feedback, supporting continuous improvement of model accuracy and user confidence. Overall, these developments position AI models at the intersection of image analytics, phenology, and agronomic decision-making, providing a robust framework for generating quantifiable and sustainable recommendations in smart agriculture *(Khose and Mailapalli, 2024).*

Systematic optimization of each stage—from data acquisition to the generation of agronomic recommendations—results in a significant cumulative improvement in overall system performance. The integration of these strategies has led to 10–25% increases in overall accuracy and 30–40% reductions in false alarm rates for disease, pest, and weed detection, thereby enhancing the efficiency of Decision Support Systems (DSS) and Variable Rate Application (VRA) technologies.

Anticipating the impact of extreme weather conditions and optimizing crop planting and rotation strategies can be achieved by processing, analysing, and modeling historical data on crop yields, weather conditions, soil types, farming practices, and market prices with AI. Based on these diverse data analyses, AI predictive models can estimate future yields, anticipate the impact of extreme weather conditions, optimize crop planting and rotation strategies, and predict which crops will be most profitable in a given year, given weather forecasts and market demand. The results of the study by *Abu Jabed and Azmi Murad (2024)* comprehensively demonstrate the transformative potential of artificial intelligence techniques and tools in improving the accuracy of crop yield estimation, ultimately improving agricultural planning and resource management. Artificial intelligence-based models offer new pathways for sustainable agriculture in a constantly evolving world, addressing the challenges posed by geographical diversity, crop heterogeneity, and changing environmental conditions.

PRECISION AGRICULTURE

The field of precision agriculture represents an innovative approach that optimizes the use of resources at the micro level, to reduce waste and increase the efficiency of agricultural processes. Through the possibilities offered by AI implemented in the intelligent management of irrigation, personalized fertilization and plant nutrition and especially the selective application of pesticides and herbicides, the degree of sustainability of agricultural production has been increased (Fig. 7).

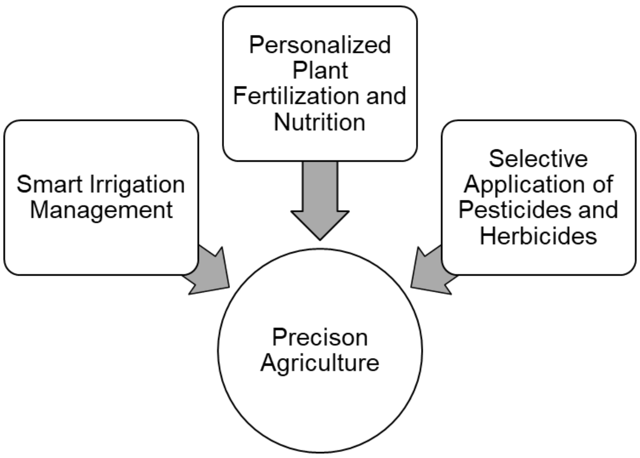

Fig. 7 - Applications of artificial intelligence in precision agriculture

In the case of intelligent irrigation management, AI-based automated systems use data from soil moisture sensors, weather stations, climate forecasts, and/or satellite data to calculate the exact water requirement for each portion of the agricultural field. Sustainable agriculture depends on efficient water management, and the integration of contemporary technologies such as artificial intelligence and the Internet of Things (IoT) into irrigation systems offers creative ways to maximize resource utilization (*Hussain et al., 2024; Abdelmoneim et al, 2025*). Through various optimization algorithms, the system decides when and how much to irrigate, delivering water only where it is needed. This significantly reduces the overall water consumption required for irrigation in addition to reducing the energy used to pump water into irrigation systems. Moreover, due to their versatility, automatic irrigation systems based on AI optimization algorithms can easily adjust the operation of irrigation installations and equipment depending on the type of crop, the plant growth phase and local environmental conditions. Experiments carried out by *Rojas et al. (2024)* showed that by connecting an irrigation system to IoT systems, a reduction in related costs by 33.8% was achieved for a 2-hectare crop of blueberries (Fig. 8). Also in this regard, *Morchid et al. (2024)* propose a complex solution for automating the irrigation process, which can provide a multitude of data related to the need to carry out the irrigation process and also transmit messages and information in real time to quickly reactivate the farmer. *Raouhi et al. (2023)* presents a digital application based on artificial intelligence (AIDSII), which leverages IoT-based precision agriculture and CNN-LSTM models, providing a complete feedback system through mobile and web technologies, allowing farmers to automate, optimize and streamline irrigation processes.

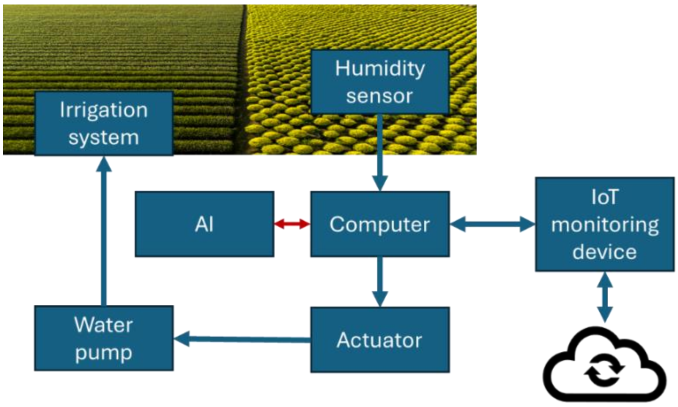

Fig. 8 - Schematic of an AI-based intelligent irrigation system (*adapted from Rojas et al, 2024*)

The results of a comprehensive analysis by *Younes et al. (2024)* demonstrate the performance capability of machine learning (ML) techniques that outperform conventional approaches. However, the use of machine learning models in smart irrigation systems is still limited, and further efforts are needed to produce well-designed and, most importantly, broadly applicable results. The application of AI tools through time series analysis in the study of crop quality and soil control mechanism under conditions of a precise combination of water and fertilizer is discussed by *Xing and Wang (2024)* from the point of view of the benefits of integration in agriculture (Fig. 9).

AI models are widely employed in irrigation management to optimize water consumption and enhance the efficiency of agricultural systems. The main application domains include: estimation of evapotranspiration (ETo) and crop coefficients (Kc) for determining the actual water requirements of crops (*Bounajra et al., 2024*); prediction of soil moisture content, using data from in-situ sensors (soil humidity, temperature, radiation, precipitation) and imagery captured by satellites or drones (*Alvim et al., 2022*); development of smart irrigation systems integrating sensors (soil moisture, atmospheric conditions), communication modules, and automated decision algorithms to optimize irrigation schedules and water application rates (*Nsoh et al., 2024*); design of hybrid models, combining neural networks, fuzzy logic, neuro-fuzzy systems, or algorithms such as Support Vector Machines (SVM), Random Forest (RF), and adaptive regressions, particularly effective under incomplete data or nonlinear relationships (*Dolaptsis et al., 2024*); predictive control and multi-objective optimization of irrigation management, leveraging weather forecasts and soil state information to maximize productivity and minimize water losses through Model Predictive Control (MPC) approaches (*Liu et al., 2025*); Reinforcement Learning (RL) for adaptive decision-making, enabling dynamic adjustment of irrigation volumes based on varying agroecosystem states (*Del-Coco et al., 2024*). Given the increasing risk of drought, automation of irrigation systems and the generation of AI-based climate reports through the processing of IoT data (temperature, humidity, soil moisture, etc.) have become essential for efficient water resource management. These systems provide advanced analytics and predictive recommendations that support the adaptation of agriculture to increasingly severe climatic phenomena (*Gaitan et al., 2025*).

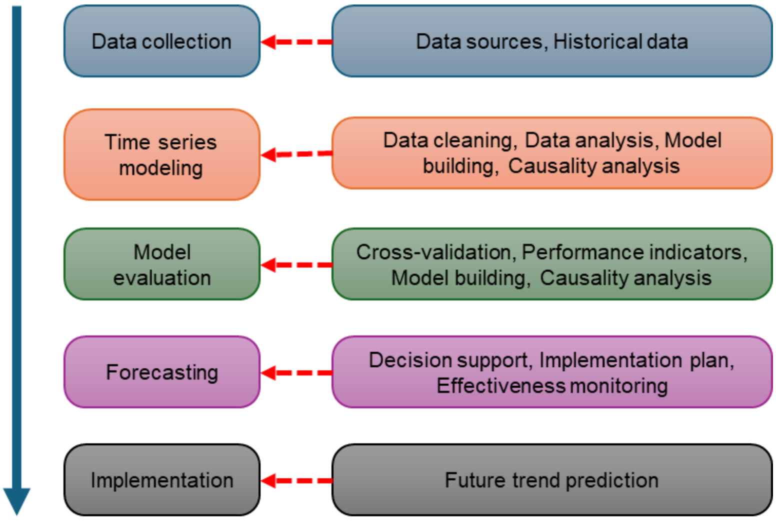

Fig. 9 - Integration of an intelligent system for study of crop quality
(*adapted from Xing Y and Wang X, 2024*)

By integrating water quality indices (total salinity, *Sodium Adsorption Ratio* – SAR, water pH, and specific toxic ions such as Cl^-, B, and Na^+) together with soil characteristics (texture, field capacity, permeability, and initial salinity level) into AI models, soil salinization risks can be predicted at early stages. *Patel et al. (2002)* highlight the advantages of employing Artificial Neural Networks (ANNs) for predicting salt accumulation and determining the optimal irrigation volume required to maintain a balance between crop water demand and soil protection. *Suleymanov et al. (2023)* propose a regional-scale salinization risk mapping approach using satellite and agrometeorological data, applying Machine Learning algorithms (Random Forest – RF) that achieve moderate to high predictive performance in modelling the spatial distribution of soil properties. Comparative analyses of hydrological models demonstrate that the HYDRUS model provides the highest accuracy in simulating soil–water–plant interactions (*Marshall et al., 2025*). Furthermore, integrating the HYDRUS solute transport model with neural networks or genetic algorithms for optimizing irrigation and soil leaching schedules enables precise estimation of leaching requirements.

There is extensive research focused on the optimization of the functional parameters of irrigation systems. *Seyedzadeh et al. (2019)* developed a simulation method for irrigation flow uniformity as a function of water temperature and operating pressure in drip irrigation systems, employing AI models such as Artificial Neural Networks (ANN), Neuro-Fuzzy Sub-Cluster (NF-SC), Neuro-Fuzzy k-Means Clustering (NF-FCM), and Least Squares Support Vector Machine (LS-SVM). The results demonstrated that all these AI-based models, used to simulate the relationship between emitter discharge rate and nominal flow rate, achieved acceptable prediction accuracy when using as input variables: operating pressure (0–240 kPa), water temperature (13–53 °C), discharge coefficient, pressure exponent, and nominal discharge rate. The models yielded a mean absolute error (MAE) of 8.8%, indicating reliable performance for modelling irrigation flow uniformity under variable operating conditions.

González Perea et al. (2018) proposed a predictive model of farmers' behaviour based on Artificial Neural Networks (ANN), fuzzy logic, and genetic algorithms, aimed at analysing irrigation water consumption. The model was validated for rice, maize, and tomato crops in farms located in southwestern Spain. The authors demonstrated that irrigation water requirements are influenced not only by agroclimatic and technical factors but also by the human factor, namely farmers' decisions and behavioural patterns. Therefore, it is necessary to raise farmers' awareness of their role in reducing water consumption through training programs, local demonstrations, and pilot initiatives. Integrating such socio-economic and behavioural factors into AI models for integrated agricultural resource management enables a more realistic representation of the decision-making process and enhances the sustainability of irrigation and water-use strategies.

Sustainable nutrient management is essential for increasing or maintaining crop yields, being one of the most important production directions on which the yield and quality of agricultural products depend (*Zhang et. al., 2020; Noulas et. al., 2023*). The process of personalized plant fertilization and nutrition starts from the analysis of soil maps, the determination of nutrient deficiencies and plant health data, In their paper *Dobermann et al. (2022)* show that critical actions regarding plant nutrition are related to proposals for nutrient roadmaps focused on sustainability, implementation of digital and AI solutions for crop nutrition, establishment of nutrient recovery and recycling processes as well as development of climate-smart fertilizers. Based on the analysis of these variables, AI algorithms can further create variable application maps for different fertilizers. Thus, the amount of fertilizer is adjusted in real time and applied only where needed (both over-fertilization, which leads to groundwater pollution over time, and under-fertilization, which leads to a decrease in production yield, are prevented).

Malashin et al. (2024) classified agricultural crops according to their macronutrient requirements (N, P, K). The authors developed an AI-based yield prediction model integrating data on crop nutrient demands, soil chemical properties, and climatic factors. The model employs Deep Neural Networks (DNN) combined with Genetic Algorithms for system parameter optimization. The obtained results ($R^2 = 0.92$) demonstrate a high level of model accuracy.

Jeevaganesh et al. (2022) developed an AI-based model integrating an AdaBoost algorithm for crop yield prediction by combining meteorological data, N–P–K levels, soil structure, and pH, along with a RF algorithm for generating fertilizer management recommendations. The model, validated using data from the ten most cultivated crops across India, achieved a prediction accuracy of 82%.

Gao et al. (2023) proposed three ML models employing RF, Extreme Random Tree (ERT), and Extreme Gradient Boosting (XGBoost) algorithms to predict yields based on historical data from maize, rice, and soybean crops. The comparative analysis revealed that the ERT model exhibited the highest predictive performance ($R^2 > 0.75$). The authors estimated that optimizing fertilization strategies based on the proposed model could increase crop yields by 23.9% for maize, 13.3% for rice, and 20.3% for soybean.

Li and Yost (2000) introduced an AI-based nitrogen fertilization optimization method aimed at increasing yields, reducing costs, and mitigating groundwater pollution caused by nitrate leaching. The model generates and evaluates multiple split-application scenarios (small, frequent doses) compared to conventional methods, based on the nitrogen cycle within the soil–plant system. The results indicate a reduction in nitrate leaching from 36 to 7 kg N ha^{-1} and an increase in profit from USD 570 to USD 935 ha^{-1} for maize cultivation.

Khaliq et al. (2025) presented a comprehensive soil–crop–irrigation–fertilizer management system integrating DL, IoT, and Explainable Artificial Intelligence (XAI). The findings demonstrate that DL models - TabNet Regressor for soil analysis (R^2 = 98.7%), Sparse Weighted Fusion Transformer (SwiFT) for crop recommendation (R^2 = 98.75%), Transformer-based Tabular Learning (TTL) for irrigation optimization (R^2 = 99.13%), and TabNet Classifier for fertilizer management (R^2 = 99.3%) - achieve exceptionally high predictive accuracy. The study concludes that these models can provide substantial decision support for irrigation scheduling and nutrient management.

Similar to the process of personalized plant fertilization and nutrition is the process of selective application of pesticides and herbicides. Finding a balance between the benefits of pesticide application and the preservation of our ecosystems is crucial to ensuring sustainable agriculture, as the extensive use of pesticides has raised concerns about the environment and human health (*Gupta, 2023*). Agricultural vehicles (land or air) equipped with computer vision systems and AI interpretation and optimization algorithms can accurately identify weeds or areas infested with pests. In this way, instead of pesticides or herbicides being applied uniformly across the entire agricultural field, the AI system directs the treatment only to the affected plants or areas, drastically reducing the volume of chemicals used. This not only lowers costs for farmers but also minimizes the negative impact on the environment and human health.

Recent research demonstrates that AI models, when integrated with precision spraying technologies (e.g., spot-spraying, Variable Rate Application – VRA, UAV sprayers, CNN/LiDAR-assisted sprayers), can substantially reduce pesticide and herbicide consumption without compromising treatment efficacy. Notable results include: a 2.3-fold reduction in pesticide and herbicide costs for soybean and wheat crops in Brazil through spot-spraying technologies (*Zanin et al., 2022*); a 47% reduction in post-emergence herbicide use via early site-specific spraying during the 2–4 and 6–8 leaf stages of maize, across four experimental fields in southwestern Germany, based on weed infestation maps generated through CNN-based (MobileNetV2) classification of UAV-acquired RGB imagery captured 2–4 days before spraying (*Allmendinger et al., 2024*); and a 30.1% reduction in chemical agent usage for wheat achieved through LiDAR-assisted VRA drone spraying systems (*Liu et al., 2025*). Studies conducted in vineyards and orchards show that early detection using CNN/YOLO-based analysis of imagery captured by in-field or drone-mounted cameras enables targeted interventions, effectively reducing the need for broad-spectrum preventive treatments. The integration of these systems with population forecasting models further enhances intervention efficiency (*Wu et al., 2025*). Moreover, intelligent spraying systems (spot-spraying/VRA), supported by AI-driven detection and multisensory data fusion, can significantly decrease the overall volume of applied substances — with reductions ranging from 20–30% in LiDAR/RGB-D experimental studies to over 70% in commercial ultra-precision spraying systems (*Salcedo et al., 2021*).

AGRICULTURAL ROBOTICS

The unprecedented development of robots, especially autonomous ones, provides the necessary opportunities to eliminate/reduce physical tasks in agriculture. By integrating AI techniques and tools into the construction and operation of agricultural robots used for sowing, planting, harvesting and managing diseases and pests, it is possible to increase the efficiency of the agricultural process with minimal human intervention (Fig. 10). The integration of AI into autonomous robots transforms the way physical tasks in agriculture are performed, increasing economic efficiency and reducing dependence on manual labour.

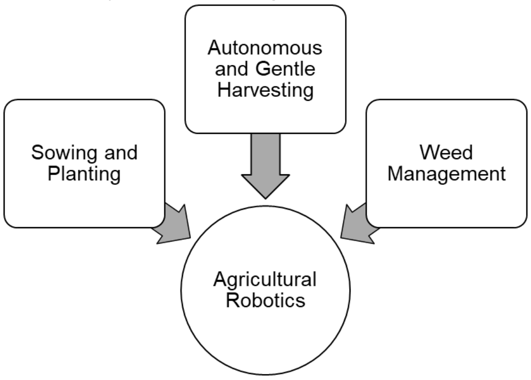

Fig. 10 - Applications of artificial intelligence in agricultural robotics

In terms of sowing and planting processes, autonomous robots have been developed that can navigate the field with sub-centimetre precision. Based on these performances, an optimal distance between plants and a uniform planting depth can be ensured (and especially a constant in these two dimensions of the processes), which ultimately leads to better germination and uniform growth of crops. *Lu et al. (2024)* proposed an AI segmentation algorithm used to separate the adhering green onion seeds and count the number of green onion seeds in each hole to improve the quality of the sowing process. The results showed that the average relative error of the system's qualification rate is 2.24%, and the average absolute errors of the reseeding rate and the emptying rate are 1.31% and 0.71%, respectively. The absolute error of the average particle number is 0.025 at an overall accuracy rate of the integrated sowing quality detection of 98% (with an average processing time per image of 0.91 s).

The development of robots capable of harvesting delicate crops such as strawberries, tomatoes or peppers is one of the most impressive technical achievements of our time. These robots use computer vision and deep learning AI algorithms to identify ripe and ready-to-harvest fruits and carefully pick them, avoiding damage. This is particularly valuable in the context of two major problems facing the agricultural sector: labour shortages and the need to reduce post-harvest losses in order to streamline economic costs. There are already AI-equipped robots in agriculture that can distinguish between cultivated plants and weeds (via computer vision). Instead of applying herbicides to the entire agricultural field, some robots use mechanical arms equipped with hot bio-oil nozzles or high-precision lasers to physically eliminate only weeds, offering an environmentally friendly alternative to total chemical control.

ANIMAL HEALTH AND LIVESTOCK

In addition to the crop agricultural sector, the introduction of AI techniques and tools in the livestock sector contributes significantly to animal welfare, production optimization and disease prevention in livestock farms through monitoring operations of animal behaviour and health, diet and nutrition optimization, disease prediction and prevention (Fig. 11).

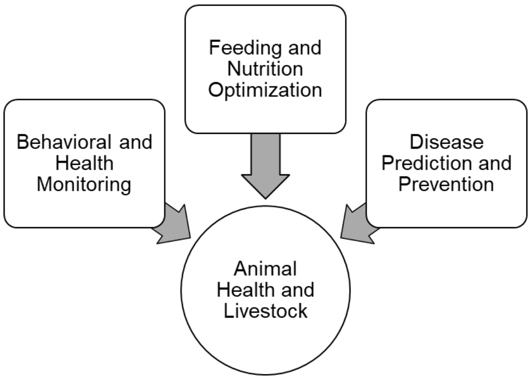

Fig. 11 - Applications of artificial intelligence in animal health and livestock

Behavioural and health monitoring is achieved through the use of smart cameras and sensors, equipment that continuously monitors the behaviour of farm animals (cows, pigs, poultry). AI algorithms analyse the data obtained to detect anomalies, such as changes in feeding patterns, activity levels, posture or vocalizations, which can indicate stress, illness or even imminent birth. Automatic alerts that can be generated based on these real-time analyses allow farmers to intervene quickly, reducing losses and improving animal welfare. Animal face recognition is of significant importance for modern intensive animal husbandry, and for this purpose *Zhang et al. (2024)* proposed an improved AI tool based on the ResNet50 network. Experimental results show that the new model (ResNet-SFR) outperforms traditional methods and other DL models, achieving a recognition accuracy of 96.6% on the sheep face image dataset. Furthermore, compared to ResNet50, the proposed model exhibits a 2.4% improvement in F1 score and a 2.3% improvement in accuracy.

Furthermore, AI-based systems obtain and analyse individual data about each animal (e.g. age, weight, breed, activity level, lactation/gestation stage) and can customize feed rations based on these parameters. This precision feeding maximizes feed conversion, reduces feed waste, and optimizes growth or production of related products (milk, meat, eggs). Moreover, automatic sensors and actuators can even detect how much each animal eats and drinks on an individual level, automatically adjusting the amounts set/optimized by the farmer based on AI analysis. An important activity in the specifics of the animal breeding process is also the activity of disease prediction and prevention. By integrating data from sensors (body temperature, heart rate), laboratory analyses, meteorological information, and epidemiological data, AI predictive models can identify the risks of certain infectious or metabolic diseases based on patterns. This predictive capacity is a very important factor because it allows farmers to take preventive measures, through actions (manual or automatic) in real time related to adjusting ventilation, isolating suspicious animals, or administering early treatments, limiting the spread of diseases throughout the farm.

DL models, particularly CNN and Recurrent Neural Networks (RNN), have demonstrated superior performance in the visual and behavioural monitoring of livestock. For instance, CNN-based approaches enabled body weight estimation in pigs with an error rate below 2% (*Kwon et al., 2024*) and mastitis detection in dairy cows with over 90% accuracy (*Liu et al., 2025*). These outcomes have a direct impact on reducing production losses and veterinary costs through early interventions and optimized nutrition management.

RL models have been successfully applied to automated feeding systems and agricultural robot management, achieving cost reductions of 8–12% and more efficient resource utilization (water, feed, energy) *(Pawar et al., 2024)*.

Conversely, Bayesian models and traditional ML algorithms (RF, SVM) remain widely used for automated diagnosis of cattle and swine diseases, achieving 85–95% accuracy in detecting mastitis or digestive infections, while reducing veterinary treatment costs by 20–30% *(Pfrombeck et al., 2025)*.

A major technological advancement is represented by multimodal models and the digital twin concept, which integrate video, acoustic, and sensor data to create real-time virtual representations of animals (*Han et al., 2022; Zhang et al., 2025*). These systems provide a holistic view of physiological and behavioural states, enabling proactive interventions and animal welfare optimization, while reducing economic risks.

Big data and ensemble learning models (XGBoost and Deep Fusion) have proven effective for integrated farm management. They can reduce total operational costs by 10–20% and increase productivity by 15–25% by simultaneously correlating environmental, nutritional, and physiological parameters *(Chase and Fortina, 2023)*. In advanced smart dairy and smart pig feeding systems, annual savings of up to USD 40,000 and substantial reductions in greenhouse gas emissions have been reported *(Pomar, 2019)*.

Overall, the correlation between AI models and achieved benefits is positive and exponential up to a certain technological threshold. While increased algorithmic complexity enhances prediction accuracy and decision-making efficiency, marginal returns may decline in the absence of robust data infrastructure. Nevertheless, recent literature confirms that the integration of AI in animal husbandry leads to lower operational costs, higher productivity, and improved animal health and welfare, thereby reinforcing the strategic direction of smart and sustainable agriculture *(McNicol et al., 2024)*.

SUPPLY CHAIN MANAGEMENT

Optimizing the flow of agricultural products from farm to consumer ensures efficiency, traceability and reduces losses, and in this context, AI plays an important role through its ability to propose models for optimizing all these processes (Fig. 12). The forecast of demand and prices in the market is achieved by analyzing large volumes of existing data related to: market, consumption trends and economic events. These types of data are taken and introduced into various AI algorithms, which can forecast with increased accuracy future trends in demand/supply for various agricultural products and price fluctuations. This information is vital for farmers in economic business planning, in planning the type of crops grown, setting prices and managing stocks.

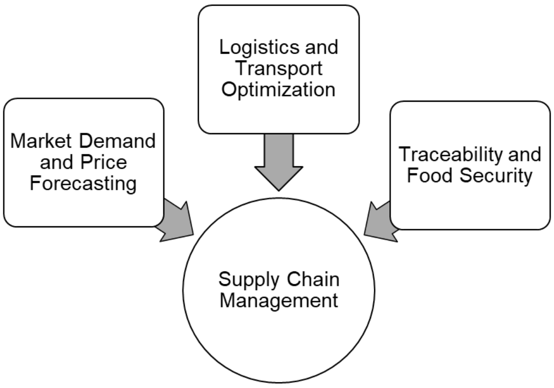

Fig. 12 - Applications of artificial intelligence in supply chain management

Due to its ability to assist in tasks such as fault diagnosis and detection, system commissioning, and agricultural energy efficiency assessment of a crop production system, the expected yield of agricultural production is an important consideration in energy management. The main aim of the study by *Nabavi-Pelesaraei et al. (2021)* was to suggest a technique for predicting agricultural yields from an energy perspective by modeling energy consumption and forecasting energy production for various agricultural products using ANN and adaptive neuro-fuzzy inference systems (ANFIS). *Nguyen et al. (2024)* emphasize that by integrating artificial intelligence into the supply chain, farmers in Vietnam can make more informed decisions, optimize resources, and minimize risks, and artificial intelligence can help bridge the gap between smallholder farmers and the market by facilitating better access to information. Agricultural products have as their purpose to be offered to the market so that the transport of products to interested markets represents another area of interest in agriculture. The optimization of logistics and the transport of products can be optimized through AI techniques for maximum efficiency of the exploitation of means of transport with a minimum of fuel consumption. Also, transport routes for perishable products (existing especially in agriculture and the food industry) can be optimized, taking into account traffic conditions, weather forecasts and loading capacity and type of vehicles. Intelligent systems can (at a complex level) manage delivery schedules, reducing transit time and ensuring that products arrive at their destination in optimal conditions, thus minimizing losses in the supply chain.

AI applications are also being developed that optimize the dynamics of specific processes within agricultural warehouses. In this regard, the study by *Lv and Li (2025)* proposes a method that uses a target detection algorithm to optimize the dynamic characteristics of robots in an agricultural warehouse. The method initially uses the YOLOv5 target detection algorithm to recognize dynamic targets in images captured from the warehouse environment and the final test on the TUM dataset shows that the proposed system with improved vision increases the localization accuracy by 91.47% compared to other AI tools in highly dynamic scenes.

The importance of fruit counting in agricultural production management is increasing, becoming an indispensable management tool for agricultural producers, and in this regard, a method for detecting and sorting fruits using AI methods was proposed by *Yang (2024)*. The results show that the mAP values of the proposed AD-YOLO model are 3.1% higher than those of the YOLOv8 model, reaching 96.4%. The improved tracking algorithm has 297 fewer ID switches, which is 35.6% less than the original algorithm. The multi-object tracking accuracy of the improved algorithm reached 85.6%, and the average counting error was reduced to 0.07. The R2 coefficient of determination between the actual value and the predicted value reached 0.98.

Estimating energy use targets for aquaculture is imperative to reduce carbon emissions and energy waste. Therefore, in the study conducted by *Elahi and Khalid (2022)*, target energy consumption amounts were determined to reduce environmental emissions of aquaculture farms using AI (ANN) tools. Energy use indices such as energy use efficiency, bioenergy use efficiency, and energy productivity can be improved by 20%, 16%, and 14%, respectively, if farmers use target amounts of energy inputs suggested by the AI method. Total energy and bioenergy consumption are reduced by 21% and 22%, respectively, and greenhouse gas emissions (CO2 per farm) were reduced by 23% by using optimized energy input solutions provided by AI. The application of predictive maintenance using artificial intelligence tools (machine learning models) for agricultural equipment, with the aim of increasing the inefficiency of an agricultural farm, was carried out by *Iosif et al. (2025)*. A predictive maintenance framework was developed using seven machine learning models: Isolation Forest, One-Class SVM, KMeans, DBSCAN, Autoencoders, Convolutional Neural Networks and XGBoost, to analyze the maintenance parameters of a tractor hydraulic system, with effects on optimizing maintenance schedules, reducing unplanned downtime and extending the life of the equipment AI-based technologies enable complete traceability of agricultural products, by recording and monitoring every step of the supply chain – from producer to consumer. Consumers can see the product history, information about the production farm, cultivation methods (e.g. organic or not, use of pesticides and/or herbicides, etc.) and harvest date. This increases the transparency of agricultural processes, provides consumer confidence and helps to quickly identify the source in case of food safety issues.

CONCLUSIONS

The need for the evolution of agriculture to achieve the desired quantity of agricultural products, combined with the need for these products to be produced on a sustainable basis, makes the use of AI tools and methods mandatory. The possibilities and areas of application in agriculture are vast, starting from planting, irrigation, fertilization, weeding, spraying and harvesting crops to farm management and the fusion of satellite data with those from agricultural fields. This is due to the fact that the power of AI methods in detecting, analysing and estimating data exceeds that of traditional techniques. However, it should be noted that there are still barriers that limit the large-scale incorporation of AI tools in agricultural farms, and in this regard, governments must develop, adopt and implement policies to support farmers. Several strategies that are immediately and potentially practically applicable can help farmers overcome the obstacles to integrating AI into agriculture:

- Increasing awareness and cooperation among farmers, technology providers, and policymakers
- Providing financial incentives and/or local, regional, and federal grants to farmers to help them cover the high upfront costs of AI technology, increasing funding for building internet access and IT infrastructure in rural areas.
- Education and training programs (through specialized workshops and courses) are also needed to close the current skills gap among farmers.

These immediate initiatives can show farmers the real benefits of AI in agriculture, which can simplify their adoption of these cutting-edge technologies. Creating AI models and tools that are easy to use and require little technical knowledge can help farmers integrate AI into their daily operations. Clear policies and regulations should be implemented to protect farmers' production data, to address concerns about data privacy and ownership.

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