AI for Sustainability: Activities of the CINI-AIIS Lab at University of Naples Federico II

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Abstract

Sustainability is pivotal to global development, aligning closely with the United Nations' goals for a sustainable future. This paper introduces and discusses the perspectives and initiatives undertaken in these regards by the CINI AI-IS (the Italian National Consortium for Informatics, Artificial Intelligence and Intelligent Systems) Lab at the University of Naples Federico II. We will first introduce the DroughtScope project, currently on board the Kanyni Australian satellite to exploit hyperspectral data to detect early water stress in crops and optimize water resource management. We will then describe the PIVA project, addressing the challenge of missing data in complex systems, which occurs frequently in environmental domains, using Physics-Informed Variational Auto-Encoders to prevent model collapse. Additionally, the impact of Agriculture 4.0 on farmer health and workplace safety is discussed, examining the challenges and opportunities presented by advanced technologies. Finally, the paper considers the environmental and ethical implications of AI's carbon footprint, emphasizing the need for a balanced approach to technological advancement and environmental accountability.

Keywords

Synthetic data, Carbon footprint, Ethics, Human-Centred AI

1. Introduction

Advancements and integrative applications of artificial intelligence (AI) in agritech and environmental sustainability are becoming increasingly important as the global community seeks innovative solutions to pressing environmental challenges. The integration of AI technologies in agricultural and environmental contexts promises to enhance efficiency, reduce resource waste, and improve decision-making processes, aligning with several of the United Nations Sustainable Development Goals (SDGs), such as responsible consumption and production (Goal 12) and climate action (Goal 13) [1]. Artificial intelligence offers a transformative potential for the agricultural sector by optimizing resource use and maximizing output, thereby addressing food security and economic sustainability. For instance, AI-driven systems can predict crop yields, monitor crop health through real-time data, and provide precise inputs regarding irrigation and fertilization, significantly reducing unnecessary resource expenditure and environmental impact.

In environmental management, AI technologies are critical in monitoring ecosystem health, predicting environmental changes, and facilitating more informed decisions about natural resource management. AI's capability to process and analyze vast amounts of environmental data enhances our ability to respond to climate change, manage natural disasters, and protect biodiversity. However, the application of AI in sustainability also raises important ethical and practical challenges, including the risk of increased energy consumption, potential biases in decision-making processes, and the implications for employment in traditional farming and environmental conservation roles. It is essential to address these challenges by developing AI solutions that are not only effective but also equitable and inclusive.

In this paper, we will thus introduce and discuss the perspectives and initiatives undertaken on responsible and reliable AI by the CINI AI-IS (the Italian National Consortium for Informatics, Artificial Intelligence and Intelligent Systems) Lab at the University of Naples Federico II, specifically focusing on the activities involving the members of the PICUS Lab[1] as part of the AI-IS Node. To this aim, Section 2 describes the DroughtScope project, a finalist in the ESA's OrbitalAI IMAGIN-e competition[2], using hyperspectral data to optimize water resource management through early detection of water stress in crops and the generation of alerts for risk areas. Section 3 discusses the use of AI for cows' mastitis detection, an inflammatory condition of the udder causing critical issues for dairy milk and animal health. Section 4 describes the PIVA project, focusing on missing data imputation

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[1]https://picuslab.dieti.unina.it/
[2]https://platform.ai4eo.eu/orbitalai-imagin-e

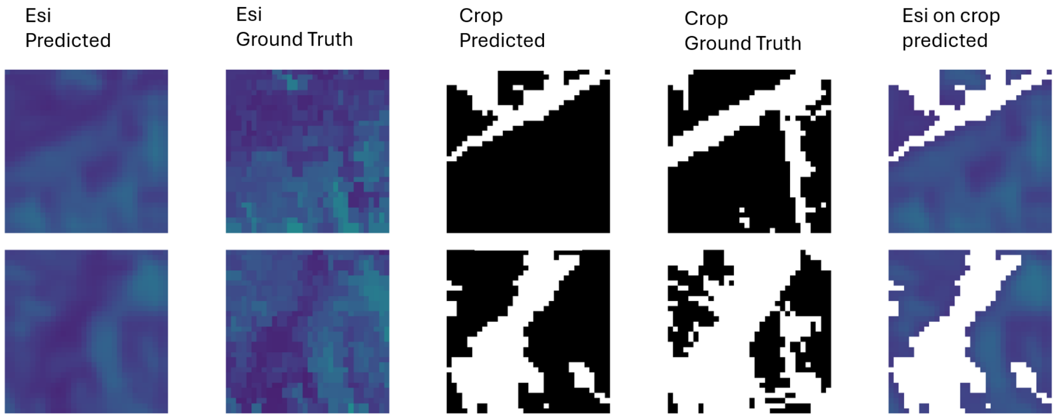

Figure 1: Raster of prediction and ground truth of the DroughtScope project.

in complex systems by means of Physics-Informed Variational Auto-Encoders. Section 5 focuses on the challenges and opportunities for improving farmers' well-being and productivity in the era of Agriculture 4.0. Finally, Section 6 analyses the AI environmental impact, particularly focusing on the carbon footprint of large-scale AI models.

2. DroughtScope project

The DroughtScope project, which appears among the finalists in the OrbitalAI IMAGIN-e competition organized by the European Space Agency (ESA), focuses on identifying early water stress conditions in crops to optimize water resource management. Utilizing hyperspectral data from IMAGIN-e, DroughtScope estimates evapotranspiration (ET) at a plot scale, enabling the creation of synthetic indicators for early detection of water stress. The project employs a multi-task deep-learning network to produce a real-time crop/no crop classification map and the Evaporative Stress Index (ESI) product. The project uses open data from the ESA WorldCover dataset for ground truth in crop mapping. Additionally, ECOSTRESS data, with a spatial resolution of approximately 70 meters, are used for ESI and are rescaled to 45 meters to align with the input hyperspectral data. The DroughtScope's architecture is designed to economize memory usage by sharing a single encoder across multiple tasks and leveraging a feature-based Knowledge Distillation (KD) technique. This project is currently on board the Kanyni Australian satellite. Some preliminary results are reported in Table 1, while Figure 1 shows some predictions made by the model.

accuracy	recall	precision	f1	model size
0.8	0.7	0.7	0.7	90 MB

Table 1
Performance of the DroughtScope project.

3. Data Analysis over Mastitis Detection

Mastitis is a critical issue for dairy milk and animal health. It is an inflammatory condition of the udder which effects economically reduces milk yield. Several methodologies, biological and new AI-based mastitis detection use machine learning algorithms and artificial intelligence to analyse data from multiple sources, such as milk production records, udder health parameters and sensor readings, to identify patterns that indicate the onset of mastitis in dairy cows. By continuously monitoring and analysing these data points, AI systems can provide early and accurate detection of mastitis, enabling timely intervention and optimisation of dairy herd health and

Table 2
An overview of recent works on mastitis detection.

Reference No.	Specific Problem	Techniques	Problem Solution	Models
[2]	Buffalo Mastitis Detection disease	The uddar size feature of buffalo is fused with temperature feature. To automatically detect uddar and eye of buffalo need neural network model YOLO7 and extract corresponding temperature and create temperature feature vector. CenterNet check the size of uddar and create size feature vector.Fused temperature feature vector and size feature vector.SVM(support vector machine) measure the degree of mastitis.	Automatic diagnosis of early stage mastitis in buffalo.Optimal AI-baed management of commercial farms	Neural Network YOLO7,CenterNet,SVM
[4]	Buffalo Mastitis Detection disease	Ultrsonography images of buffalo for training deep learnig model, EfficientNet,Polyloss,Convolutioanl block attention module, Somatic cell count	Buffalo Mastitis Detection combination of deeplearnig model and ultrasound images	Ultrasound uddar images+Efficientb3 network+CBAM+Somatic cell count+Polyloss generete a model for mastitis detection
[5]	Buffalo mastitis detection disease	Thermal infrared mastitis detection technology automatically segments key parts of the cow's eyes and udder in thermal infrared image segmentation technology. CLE−UNet (Centroid Loss Ellipticization UNet) semantic segmentation algorithm, ECA (efficient channel attention), Lovasz softmax loss function, FLIR tools.	The cow thermal infrared acquisition system, Accurate detection of cow mastitis in large-scale dairy farms	CLE-UNet Network Model
[3]	Mastitis detection based on udder characteristics and temperature.	The datasets used include data collected from the udder by four flex sensors and one temperature sensor. Machine learning classifier training includes Decision Tree (DT), Naive Bye (NB), Support Vector Machine (SVM), K−Nearest Neighbour (K−NN) and Random Forest Algorithm (RF)	The use of machine learning classifiers to detect cow diseases from images and associated metadata	Classification Model includes RF,SVM,KNN,NB and DT
[6]	Machine learning analysis to predict the presence or absence of subclinical mastitis in Italian buffaloes	Prediction model developed using four different machine learning algorithms Generalised linear model, support vector machine, random forest and neural network, Support Vector Machine to predict high or low somatic cell	Machine learning methods applied to improve subclinical mastitis prediction model	Subclinical mastitis prediction models include Generalised Linear Model, SVM, an algorithm based on decision tree(RF), pattern recognition.

productivity. In recent years, researchers have more and more using AI for detecting mastitis in the early stages of the disease. In 2023, an automatic detection method for dairy cow mastitis using the fusion of udder temperature and size features based on deep learning was proposed [2]. The author used the YOLO7 model, centre network and Support Vector Machines in his research, showing promising performance in the early detection of mastitis. In the same year, the Cina Agriculture University showed that thermal infrared technology combined with a deep CLE-Unet model can significantly improved the detection accuracy of mastitis [3]. More recently, deep learning combined with buffalo udder ultrasound was used for the first time to detect mastitis with the aim of establishing an accurate, fast and inexpensive method to detect buffalo mastitis instead of routine laboratory examination [4]. The model is suitable for mastitis detection and can be used in a small dairy farm, but still needs more deep learning methods to detect the disease more finely. Besides the reported example, Table 2 reports and details other approaches recently used for the task.

4. The Piva project

In the era of data-driven decision-making, the quality and completeness of data play a crucial role across diverse fields, ranging from medical to industrial and environmental applications. In all these cases, missing data is a frequent problem that can arise for various reasons, including sensor malfunctions or human errors. Based on the particular underlying reason, the phenomena of missing data are categorized into three distinct mechanisms: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). MCAR occurs when data missingness is entirely independent of observed or unobserved variables. MAR happens when the probability of missingness is related to the observed data but not the missing data itself. Finally, MNAR arises when the missingness is related to the unobserved data.

Over the years, different approaches have been proposed to perform missing data imputation, i.e. the reconstruction of missing pieces of information starting from available ones. As for several other domains, recently Deep Learning (DL) solutions are becoming more frequent. However, a significant challenge with DL-based systems, such as those based on Variational Auto-Encoder (VA) [7, 8], is their susceptibility to model collapse, where results often converge to median values. As this would make the imputed data statistically not compliant with the underlying physical phenomena, it is crucial to develop systems robust against this issue.

The PIVA (Physics Informed Variational Auto-Encoder) project is a solution specifically designed to prevent model collapse. To this aim, PIVA incorporates a dual mechanism approach, utilizing both physical constraints and a masking technique. It is structured on a Variational Auto-Encoder (VAE) architecture where constraints are integrated into the loss function to guide the network towards adhering to essential physical and statistical parameters. These include entropy conservation, summation constraints across variable groups, control over covariances, and adherence to the Wasserstein distance. The technique of conserving entropy in both generated and observed variables has been demonstrated to be particularly effective in mitigating model collapse. Additionally, PIVA adopts a novel data masking strategy inspired by the method used in Bert. Unlike traditional Denoising Auto-Encoders that focus on reconstructing data from noise-altered inputs, PIVA's strategy concentrates on accurately predicting masked data while ensuring compliance with the constraints imposed on these data points. This approach is pivotal for achieving dependable data imputation and enhancing the overall robustness of the model.

5. Farmer Health in the Era of Agriculture 4.0: Challenges and Opportunities

In the context of Industry 4.0, Agriculture 4.0 represents a crucial step in the evolution of precision agriculture. Automation, the use of drones and sensors, data collection, and artificial intelligence have enabled a more precise and efficient approach to agriculture, promising to increase production and reduce waste. Moreover, 4.0 solutions emerge in response to climate change, contributing to mitigating its negative effects on crop yield, management difficulties, and farmer well-being [9]. Undoubtedly, the advent of Agriculture 4.0 marks a significant breakthrough in the agricultural sector, traditionally characterized by a strong reliance on manual outdoor labour, presenting itself as a valuable ally for those who work the land. For example, thanks to automation and the use of advanced agricultural machinery, farmers can reduce their direct exposure to adverse weather conditions. If autonomous tractors and drones allow work in the fields even in the presence of heavy rains, extreme temperatures, or excessive heat, thus reducing the risk of weather-related diseases, optimizing agricultural processes allows farmers to also plan their activities more intelligently, avoiding the hottest hours of the day or adverse weather conditions [10]. Similarly, in terms of workplace safety, a particularly delicate issue in the industrial context, automation and the use of advanced machinery reduces the risk of accidents [11], thereby contributing to preserving the health and lives of farmers.

However, while these advancements undoubtedly offer benefits in terms of production and sustainability, it is essential to recognize and address the potential negative effects on farmers' health, particularly those of a psychological nature. The gradual replacement of traditional tasks of agricultural workers with machines and automated systems, while increasing production and reducing physically demanding work, could easily create a sense of alienation for those who have dedicated themselves to agriculture for generations. The sense of personal and cultural identity is often deeply connected to agricultural work. The perception of being an essential part of the cycle of nature, of contributing to food production and community well-being, can be shaken when machines begin to perform these roles, leading to a sense of loss of identity, which can have negative effects on farmers' mental health. Also, the risk of social isolation due to decreased human interaction can have a significant impact on mental health, causing feelings of loneliness and depression. Although Agriculture 4.0 undoubtedly brings advantages in terms of production and sustainability, it is essential to recognize and address the potential negative effects on farmers' health, particularly those of a psychological nature.

To ensure the prudent and efficient development of 4.0 solutions in agriculture, regulations and directives should be implemented to ensure a safe and healthy working environment and promote the physical and mental well-being of agricultural workers. At the same time, it is essential to develop psychological support programs, provide resources to address change and promote a culture of mental well-being within agricultural communities to preserve the health and well-being of agricultural workers. The transition to Agriculture 4.0 offers undeniable advantages in terms of efficiency and sustainability, but it is essential to consider the ethical implications in terms of social justice, environmental sustainability, and farmer health. Only through a multidisciplinary, fair, and sustainable approach, it may be possible to fully realize the potential of this technological revolution in agriculture, ensuring that the benefits are shared fairly and responsibly by all members of society.

6. The Carbon Footprint of AI: Ethics and Environmental Accountability

The widespread introduction of artificial intelligence at virtually every societal level prompts deep reflection on the consequences of the massive use of these technologies. This raises fundamental ethical questions about how we should regulate and manage these innovations to ensure a positive impact on society as a whole. A highly topical issue is the environmental impact of AI, particularly the carbon footprint of learning models. The increase in the size of artificial intelligence models, especially those based on deep neural networks (DNNs), consequently results in higher energy consumption during the training process [12]. This phenomenon is driven by the need for larger models to achieve better performance but raises concerns about the environmental impact due to increased energy consumption. The fundamental question revolves around striking a balance between AI's precision goals and the environmental impact resulting from such research. Essentially, to what extent is it ethical to pursue AI research and development focusing solely on model accuracy if it entails increased energy costs and pollution? It's a moral trade-off that requires careful balancing: on one hand, the accuracy of AI models is crucial for many applications; on the other hand, the rise in energy costs and pollution raises ethical concerns about the sustainability of this approach. Furthermore, complicating this equation is the awareness that much of AI's energy costs come from the operational use of models [13], highlighting the environmental responsibility not only of researchers and developers but also of AI companies, energy providers, and various stakeholders involved. Identifying and fairly distributing responsibilities among the various actors involved can thus be challenging, as they may have conflicting interests and viewpoints. Developers may focus on innovation and model accuracy, while AI companies may be incentivized to maximize profits, ignoring environmental impacts. Additionally, energy providers may resist transitioning to more sustainable energy sources for economic reasons.

These considerations underscore the need for a thorough reflection on responsible resource management by society as a whole to mitigate the environmental impact of AI from the perspective of ethical and sustainable progress. The consequences of artificial intelligence do not only concern the technical field. Today, ethics therefore play a central role in addressing the various challenges posed by artificial intelligence, and balancing technological progress with environmental responsibility is a particularly delicate moral issue. What seems desirable and necessary is a coordinated effort by industry, academia, governments, and civil society to find balanced solutions that take into account both technological progress and sustainability needs [14]. However, this approach requires open and transparent dialogue among all stakeholders, as well as targeted policies and incentives that promote environmental and social responsibility in technological innovation. For example, international organizations and regulatory authorities can collaborate to develop sustainability standards for AI, including environmental criteria to be respected during the development, implementation, and use of AI models (an example is the International Telecommunication Union, ITU, which has established a working group on environmental issues related to AI, tasked with developing recommendations and guidelines to promote sustainable use of the technology) [15]. In an era where technological innovation is advancing at an unprecedented pace, it is essential to consider the long-term implications for the environment and society. The adoption of AI offers enormous benefits in terms of efficiency, automation, and performance improvement, but it must be guided by ethical values and principles of social equity. This is because the decisions made today regarding the development and implementation of AI will have a significant impact on our planet and future generations. Furthermore, it is important to adopt a proactive approach in defining policies and regulations that guide the responsible development and use of AI, ensuring that the interests of society as a whole are adequately represented through a holistic and collaborative approach.

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