Sustainable AI: inside the deep, alongside the green

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Abstract
The increasingly inordinate production of productivity-enhancing technologies in today's society has led to an increased risk of damaging the environment from which key resources are derived, if conducted in an uncontrolled manner. It is therefore necessary to optimise strategies to make technological progress more sustainable. Artificial Intelligence (AI) plays a crucial role in this scenario and it is therefore crucial to consider sustainable AI as an integral step in the whole process. In this work we present the results and the topics under investigations in our laboratory focused on the responsible use of AI to meet technological improvement.

Keywords
Artificial Intelligence, Sustainable AI, Green technology

1. Introduction

Artificial intelligence (AI) is now a reality in our lives. Various definitions of AI have been given over the years, but they all have in common the idea of creating machines that can think like humans, with the intention of improving the effectiveness and efficiency of their activities and thus ultimately the quality of life [1].

Conversely, however, inordinate expansion can have a negative impact on the environment, and there is no doubt that any global and pervasive production of products (or innovation) requires attention to its impact on the environment. For instance, mass farming has been shown to impact biodiversity, mass production of clothing has an impact on the world's water reserves, and e-waste releases chemicals and poisons into the water and soil where it is dumped.

It is therefore necessary to bear in mind that any evolution of technology should be geared towards the wise choice of resources to reduce environmental impact. In these terms, *sustainable Artificial Intelligence* (AI) can help optimising productions according to the specific tasks required, developing an AI that is compatible with the preservation of environmental resources for current and future generations, through the economic models of societies, and with the fundamental social values of a given society [2].

This manuscript presents innovations developed in our institution which are boosted by AI, which aim to bring improvements to the traditional performance of specific activities as well as to optimise available resources while keeping waste and ecologically sustainable outcomes low.

2. Intelligent Transportation Systems

Intelligent Transportation Systems (ITSs) have been developed since the second half of the 20th century. Both increasing urbanization and the latest advances in technology have made it a timely and extremely relevant topic [3, 4]. ITSs aim to improve transport systems in all aspects and concern the design, analysis, and control of information technology by integrating data from different sources (e.g., GPS sensors, cameras, LIDAR systems and so on) [3]. We serve this paradigm under two directions: developing an open-source toolbox for map-matching and road pothole recognition and segmentation. The two projects can be combined to create routing software that considers road quality, enabling drivers to choose smoother routes. This could enhance driver safety and reduce fuel consumption.

2.1. PyTrack

The exponential growth of IoT devices, smartphones, smartwatches, and vehicles equipped with positioning technology, such as Global Positioning System (GPS) modules, has boosted the development of location-based services for several applications in Intelligent Transportation Systems. However, the inherent error of location-based technologies makes it necessary to align the po-

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sitioning trajectories to the actual underlying road network, a process known as map-matching [5]. To the best of our knowledge, there are no comprehensive tools that allow us to model street networks, conduct topological and spatial analyses of the underlying street graph, perform map-matching processes on GPS point trajectories, and deeply analyze and elaborate these reconstructed trajectories. To address this issue, we present PyTrack, an open-source map-matching-based Python toolbox designed for academics, researchers and practitioners that integrate the recorded GPS coordinates with data provided by the OpenStreetMap, an open-source geographic information system.

With reference to the figure 1 in a nutshell, the algorithm performs the following steps:

- Using the API exposed by Google Map, the algorithm matches each coordinate point provided by the user's GPS as input to the closest corresponding point in a navigable route on the map;
- Finds the best trajectory that links all the matched points and maintain its coherence with the street avoiding one-way streets and roundabouts in the wrong direction;
- Using the API made available by OpenStreetMap, it performs a compact oversampling of the entire space between all pairs of snapped coordinates following the best trajectory and thus generates a video with the corresponding sequence of frames oriented in the same direction as the driver would be oriented if driving.

For more information on PyTrack, users are encouraged to visit the official repository[1].

2.2. Road Quality Evaluation

We aim to improve ITS also by implementing a system to perform road condition analysis using computer vision techniques applied directly to information extracted from an onboard vehicle camera. This can serve ITSs with innovative functionalities to facilitate and improve the transportation sector with a positive return on community welfare. This technology could be applied to recognize and locate road irregularities to provide a high-level autonomous driving system with information to avoid potholes.

The current work has focused on exploring the latest computer vision methods for detecting potholes and road cracks. Specifically, the emphasis has been on using multimodal techniques, which involve using heterogeneous data sources to analyze the problem from various points of view and thus improve the model's overall performance. In addition, the focus was to find an appropriate

[1]https://github.com/cosbidev/PyTrack

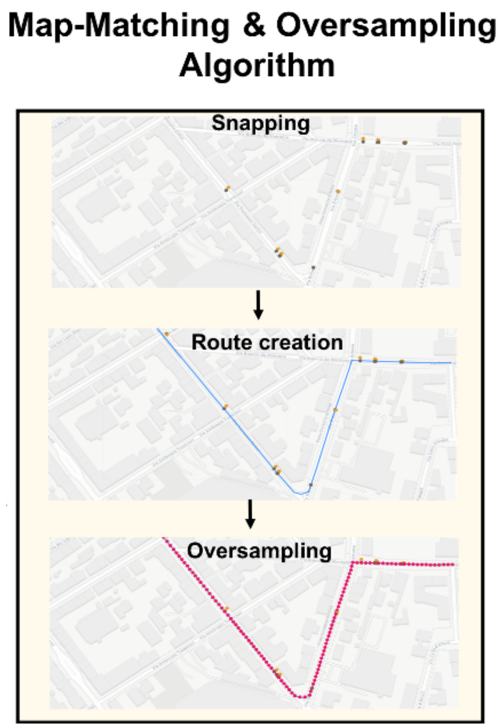

Figure 1: PyTrack application' pipeline.

experimental setup for capturing data and simulating a smart vehicle. To this end, a stereo camera was identified that could capture multimodal information, including a depth map for observing the road surface.

To complete this work, the next steps involve gathering and annotating a dataset through an acquisition phase and validating the model's performance using computer vision techniques to detect potholes. A representation of the described pipeline is depicted in 2.

3. The shift towards the Renewable Energy Sources: a photovoltaic case study

Given the combination of climate change, the need to reduce greenhouse gas emissions, and macroeconomic and geopolitical instability, the integration of renewable energy into modern power grids is steadily increasing. The shift towards renewable energy sources is crucial to a sustainable, affordable, accessible, clean, and low-carbon future, reducing polluting emissions and dependence on fossil fuels.

In this regard, photovoltaic (PV) energy is rapidly emerging as one of the world's most promising renewable

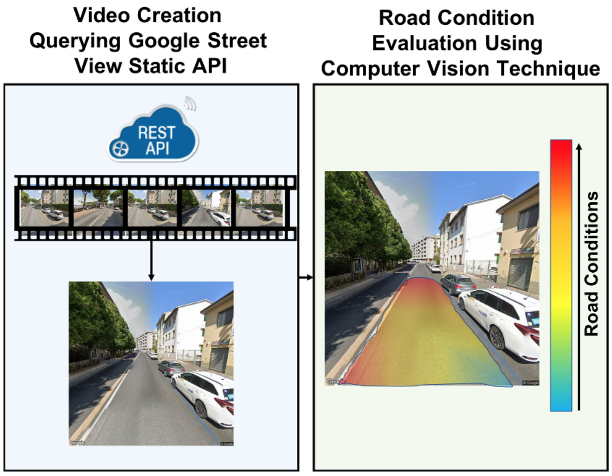

Figure 2: Road quality evaluation graphical depiction.

energy sources, playing a crucial role in accomplishing various climate protection goals [6, 7, 8], indeed, thanks to the guarantees of low carbon consumption, adaptability to different applications and the advantage of keeping installation and maintenance costs low, ascribing it as a sustainable energy source [9]. Compared to fossil fuel-derived energy, green energies are substantially more sustainable. However, their inherent intermittent nature does not guarantee constant production flows, causing imbalances in electrical grids that ultimately limit large-scale adoption [10]. Nevertheless, in recent years, with the rapid development of IoT technology, largely powered by artificial intelligence, various smart applications have been applied to many fields, and a forecasting system that simulates hourly global solar irradiance predictions has also been proposed [11, 12].

Photovoltaic energy generation forecasting could in fact help resolve these imbalances and uncertainties, facilitating the introduction of renewable energy sources into modern power grids [13, 14, 15]. Accurate forecasting of photovoltaic production emerges therefore as an essential stakeholder to realise the full potential of PV systems and provide grid operators and energy traders with valuable insights and decision-making information to optimise maintenance strategies, plan the development of new plants, mitigate operational and management challenges, and improve economic returns on investment [16].

For this reason, several methods for forecasting photovoltaic energy production have been developed recently, divisible in physics-based and data-based, in turn the latter divisible into statistics-based and AI-based.

While methods based on physical data, also known as Numerical Weather Prediction (NWP), can be used to emulate complex systems, they can often reveal a lack of flexibility and, those that rely on statistical approaches, even if they offer a good compromise between accuracy and model simplicity, may be unsuitable for discovering non-linear relationships and are highly dependent on the quality of the available data. On the other side, due to their ability to discover complex relationships, deal with unstructured data, and superior performance, AI-based models have focused the research in recent years. Among these methods, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are the most used DL-based architecture providing state-of-the-art performance in PV power forecasting [14].

In photovoltaic systems, the amount of energy produced is heavily influenced by weather factors, such as solar radiation. While deep learning methods have shown promising results in forecasting PV power production, they ignore the underlying physical prior knowledge of the phenomenon. This is where NWP-based methods can be incredibly advantageous, as they provide valuable insights about the weather factors that affect energy production and, therefore, can help improve forecasting accuracy. Despite the potential benefits, relatively few works have explored the combination of NWP and DL models [17].

In this respect we propose MATNet, a novel self-attention-based architecture for multi-step day-ahead photovoltaic power production forecasting, combining the advantages of a deep learning approach with the a priori knowledge of the phenomenon provided by physical-based models.

The contributions of this work are summarised as follows:

- We propose a novel self-attention transformer-based architecture for multivariate multi-step day-ahead photovoltaic power production forecasting. The attention mechanism is a vital part of the architecture enabling the model to focus on input data elements dynamically.

- The proposed architecture consists of a hybrid approach that combines the ability to generalise and automatically capture complex patterns and relationships in the data, typical of the deep learning paradigm, with the prior physical knowledge of photovoltaic power generation of NWP methods. By combining these two approaches, our model can achieve a more accurate and robust PV power generation forecast.
- We fed the proposed model with historical photovoltaic data and historical and forecast weather data. The historical and forecast weather data are conceptually different as they observe the phenomenon at different points in time. Therefore, the architecture handles these input branches through joint fusion performed at different levels of abstraction.
- We propose a dense interpolation module to simplify the high-dimensional representation returned by the attention-based module.
- We evaluate the model's effectiveness by comparing it extensively with the Ausgrid benchmark dataset using different regression performance metrics, ablation studies, and data perturbations. The results show that the proposed MATNet architecture with an RMSE score equal to 0.0673 significantly outperforms the current state-of-the-art methods. On the other hand, the ablation study of the different modalities study highlights the crucial role that weather forecasts play in the overall performance of our model.

4. Precision Agriculture

Before the advent of agricultural mechanisation, the very small size of plots allowed farmers to vary treatments manually. However, with the enlargement of fields and intensive mechanisation, it has become increasingly difficult to take into account the variability within the field without a revolutionary development of technologies, where crops must face several challenges arising from sub-optimal management of agricultural resources and increased pressure from biotic and abiotic stress factors, and therefore the need for a major restructuring of resources has increased, while also seeking solutions with a reduced impact on the entire ecosystem as much as possible. The proposed pipeline and consequent forecasting are depicted in Figure 4.

In the recent years, Precision Agriculture (PA) has become widespread and conceptualised as a systemic approach to reorganise the entire agricultural system towards sustainable low-input, high-efficiency agriculture. This new approach mainly benefits from the emergence and convergence of different technologies, including miniaturised computing components, automatic control, field and remote sensing, and mobile computing. The agricultural industry is therefore now able to collect more comprehensive data on production variability over time and considering different geographical areas of interest [18, 19]. The next step for the PA is to be able to respond to this variability of optimisation demands on a finer scale and thus inherent to, for example, individual crops of specific products, trying to apply mass knowledge and adapt it to detailed cases.

In these terms, an increasingly popular practice for such a task is the use of AI, as a useful and effective tool for maximising production yield, minimising waste and energy consumption. Indeed, AI in PA can involve better utilization of a farm's resources, such as fertilizers, herbicides, irrigation, and seeds allowing for the correct intervention at the right place and time. PA aims to improve crop production by maximizing yields with minimal chemical application, where, as example, a field can be divided into zones, each receiving a customized amount of resources based on different landscape types and management history [20].

4.1. Low Orchard Productivity Assessment

In this context, we are working on a PA application in the field of fruit and vegetable production. Indeed, in partnership with Zespri Kiwifruit, we are developing an AI-based application to map the Kiwifruit Vine Decline Syndrome (KVDS) phenomenon on G3 using satellite image data. Measuring the impact of KVDS on Yellow Kiwi plants is useful for assessing the expected decrease in the year's production, the quality of the fruit that will be harvested, and the prospects of production and productivity from a historical point of view. To this end, we retrieve from the Sentinel-2 satellites all the historical imaging data available for the partner farms of Zespri for the G3 project. The Sentinel-2 satellites provide 13 spectral channels in the visible/near-infrared and short-wave infrared spectral range with 10 meters spatial resolution. Starting from the spectral channels, we are computing well-known vegetation indices such as NDVI, NDMI and NDRE [21] to map the vegetation health of considered farms during time. Figure 4 shows a schematic of the developed pipeline for NDVI computation. Note that for NDVI estimation, we need from Sentinel-2 the RED and NIR spectral bands. Merging all the retrieved data points allows for estimating a multivariate time series of the considered indexes performing inter- and intra-farm statistical analysis of both. In the former case, we are

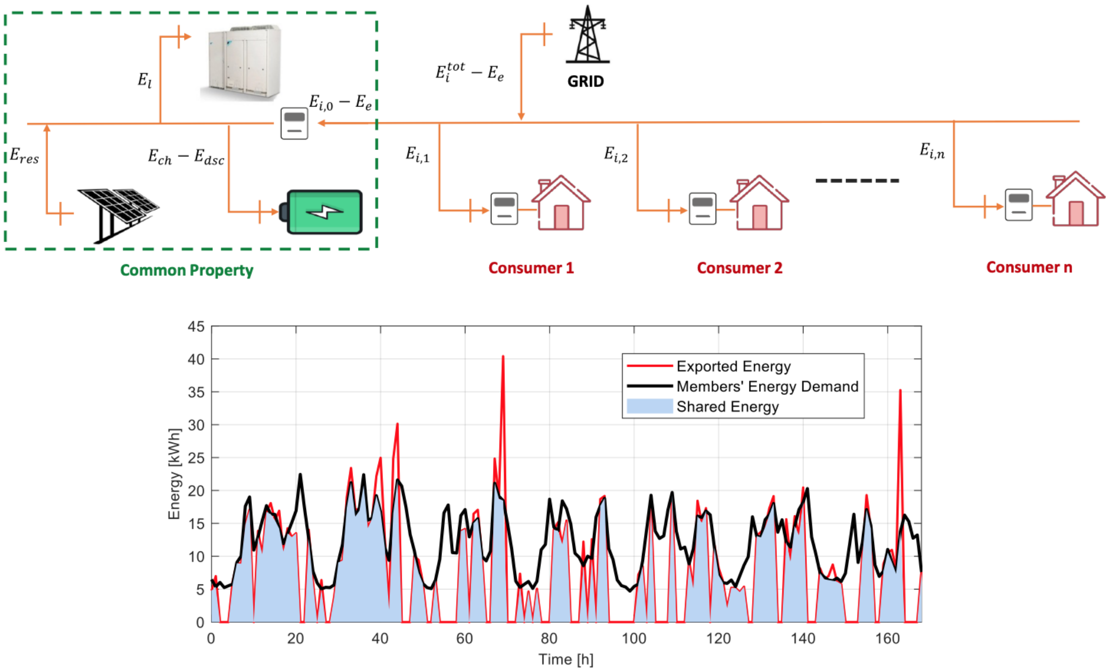

Figure 3: Example of monitoring, management and control functionalities in a commercial platform (up) and associate power consumption (down).

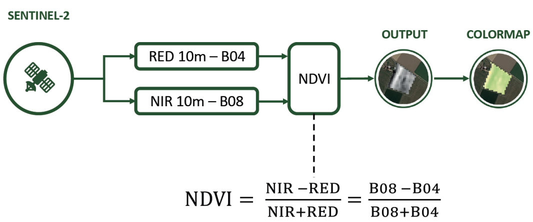

Figure 4: Data retrieval pipeline for NDVI.

considering all the farms provided by Zespri to compute a global stress indicator across the years. This analysis allows aggregating farms into stress areas giving an insight about the actual condition of KVDS. In the latter case, we aim to find local stress regions within each farm, exploiting classical AI algorithms like clustering. Finally, to visualize the obtained results, a dashboard will be developed.

As a future development, we plan to employ Generative Models to design an image-to-image translation framework to remove the presence of hail nets from the considered crops which reduces the reliability of the calculated indexes. Another possible direction relies on developing an AI pipeline to detect clouds from downloaded images to understand if they overlap or not the considered farm. This allows for increasing the amount of available data from satellites.

5. Conclusions

The technological evolution of the last few decades has produced the double effect of promoting productivity in various fields of daily life together with the risk of damaging the environment due to the uncontrolled exploitation of resources, thus requiring more sustainable progress. For our side, we have therefore presented three topics under investigation in our laboratory, namely PyTrack, an open source Python toolbox which aims to reconstruct the best trajectories starting from GPS coordinates and subsequently combine them with the images produced by the OpenStreetMap API to allow an assessment of the quality of the road ruined by potholes and cracks. As a second contribution we propose MATNet, a novel self-attention-based architecture for multivariate prediction of day-ahead photovoltaic energy production. Its evaluation against reference datasets far exceeds current state-of-the-art methods. Finally, in the field of precision agriculture, we presented a collaboration with Zespri Kiwifruit through an AI-based application with the aim of mapping the phenomenon of kiwi vine wasting syndrome over time using satellite image data.

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