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VineComputer: Automated Bud Forcing for Viticultural Productivity Forecasting

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Resumo

A crescente necessidade de uma agricultura mais eficiente e sustentável, aliada à escassez de mão de obra e à elevada variabilidade climática, tem impulsionado a adoção de tecnologias de viticultura de precisão. Neste contexto, a previsão precoce do rendimento desempenha um papel central no apoio à tomada de decisões vitícolas. Este trabalho aborda o desenvolvimento de uma estufa automatizada para forçar os botões dormentes das videiras, com o objetivo de estimar antecipadamente o potencial de rendimento, reduzindo a dependência de processos manuais e aumentando a fiabilidade das previsões. A investigação é motivada pela relevância económica e social do setor vitivinícola, particularmente em Portugal, e pelos desafios associados à aplicação manual da técnica de forçamento, nomeadamente a sua elevada variabilidade e a necessidade de mão de obra especializada.

A metodologia proposta baseia-se numa abordagem integrada que combina Agricultura em Ambiente Controlado (CEA), instrumentação e tecnologias digitais. O trabalho inclui a análise de variáveis ambientais que determinam o desenvolvimento da inflorescência, o estudo de sistemas inteligentes de controlo e monitorização de estufas e a integração de técnicas de visão computacional para a deteção e quantificação automáticas de inflorescências. São exploradas tecnologias de aquisição de imagens, métodos de processamento e algoritmos de aprendizagem automática com o objetivo de apoiar a automatização da análise fenológica e obter indicadores quantitativos de produtividade.

A automação visa aumentar a eficiência e a reprodutibilidade da técnica de forçamento de botões, permitindo um maior controlo das condições experimentais e reduzindo a variabilidade associada à execução manual. Os resultados esperados contribuem para o avanço da viticultura de precisão, demonstrando o potencial da automação e da digitalização como ferramentas fundamentais para uma viticultura mais sustentável, resiliente e tecnologicamente avançada, bem como para a futura aplicação destes conceitos noutros contextos agrícolas.

Palavras-Chave: viticultura de precisão, agricultura em ambiente controlado, forçagem dos gomos dormentes, sistemas embarcados, visão por computador, previsão de produtividade.

Abstract

The growing need for more efficient and sustainable agriculture, coupled with labour shortages and high climate variability, has driven the adoption of precision viticulture technologies. In this context, early yield forecasting plays a central role in supporting viticultural decision-making. This work addresses the development of an automated greenhouse for forcing dormant vine buds, with the aim of estimating yield potential in advance, reducing dependence on manual processes and increasing the reliability of forecasts. The research is motivated by the economic and social relevance of the wine sector, particularly in Portugal, and by the challenges associated with the manual application of the forcing technique, namely its high variability and demand for specialised labour.

The proposed methodology is based on an integrated approach that combines Controlled Environment Agriculture (CEA), instrumentation and digital technologies. The work includes the analysis of environmental variables that determine inflorescence development, the study of smart greenhouse control and monitoring systems, and the integration of computer vision techniques for the automatic detection and quantification of inflorescences. Image acquisition technologies, processing methods, and machine learning algorithms are explored in order to support the automation of phenological analysis and obtain quantitative productivity indicators.

Automation aims to increase the efficiency and reproducibility of the bud forcing technique, allowing greater control of experimental conditions and reducing the variability associated with manual execution. The expected results contribute to the advancement of precision viticulture, demonstrating the potential of automation and digitisation as fundamental tools for more sustainable, resilient and technologically advanced viticulture, as well as for the future application of these concepts in other agricultural contexts.

Keywords: precision viticulture, controlled environment agriculture, bud forcing, embedded systems, computer vision, yield forecasting.

UN Sustainable Development Goals

The United Nations (UN) Sustainable Development Goals (SDGs) constitute a global agenda to promote sustainability and global well-being. Structured around 17 goals¹, this plan aims to address today's critical challenges, including the eradication of poverty, the fight against climate change, the reduction of inequalities and the promotion of peace.

VineComputer contributes directly to several of the SDGs, in particular those relating to sustainable agriculture, technological innovation, resource efficiency and adaptation to climate change.

In context, this project has the potential to contribute to the following ones:

SDG 2 Zero Hunger: End hunger, achieve food security and improved nutrition and promote sustainable agriculture

SDG 8 Decent Work and Economic Growth: Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all

SDG 9 Industry, Innovation and Infrastructure: Build resilient infrastructure, promote inclusive and sustainable industrialisation and foster innovation

SDG 12 Responsible Consumption and Production: Ensure sustainable consumption and production patterns

¹<https://sdgs.un.org/goals>

SGD	Target	Contribution	Performance Indicators and Metrics
2	2.4	By accurately forecasting yields, growers can manage their resources (water, treatments, labour) more effectively, avoiding waste and optimising their harvest.	Degree of mathematical correlation between the inflorescence forecast generated in the greenhouse and the actual yield recorded in the vineyard at harvest time; Percentage of dormant buds that effectively sprout in the greenhouse.
8	8.2	It transforms a manual, time-consuming and analytical process into an automated task with high added value, boosting the economic efficiency of the wine sector.	Percentage of working hours saved; Time taken by the system from image capture to report delivery.
9	9.5	It introduces Artificial Intelligence and the Internet of Things (IoT) into a traditional sector, driving technological innovation in the field.	Adoption of new technologies in agriculture; The algorithm's accuracy rate in identifying inflorescences.
12	12.2	Knowing the expected crop yield in advance makes it possible to plan the precise use of fertilisers, pesticides, water and other resources, thereby reducing the ecological footprint.	Estimated reduction in the use of plant protection products, fertilisers and fuel in vineyards, calculated on the basis of precision decisions made thanks to advance knowledge of the harvest yield.

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“O que faz andar o barco não é a vela enfunada, mas o vento que não se vê.”

Mia Couto

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List of Acronyms

ABA	Absciscic Acid
CAD	Computer-Aided Design
CAN	Controller Area Network
CEA	Controlled Environment Agriculture
CM5	Compute Module 5
CNC	Computer Numerical Control
CNN	Convolutional Neural Networks
CSI	Camera Serial Interface
CSV	Comma-Separated Values
CV	Computer Vision
DC	Direct Current
DLC	Data Length Code
DO	Designation of Origin
EC	Electrical Conductivity
EPS	Expanded Polystyrene
EU	European Union
FCN	Fully Convolutional Network
FOV	Field of View
GB	Gigabytes
GPS	Global Positioning System
GPU	Graphics Processing Unit
HVAC	Heating, Ventilation and Air Conditioning
I²C	Inter-Integrated Circuit
IoT	Internet of Things
KSP	K-Shortest Paths
LED	Light-Emitting Diode
MLP	Multilayer Perceptron
NC	Normally Closed
NDVI	Normalized Difference Vegetation Index
PAR	Photosynthetically Active Radiation

PBN	Primary Bud-Axis Necrosis
PCB	Printed Circuit Board
PDAF	Phase Detection Autofocus
PFC	Personal Food Computer
PTC	Positive Temperature Coefficient
PWM	Pulse Width Modulation
RANSAC	Random Sample Consensus
RGB	(Red, Green, Blue)
RPM	rotations per minute
RTC	Real-Time Clock
SDGs	Sustainable Development Goals
SIFT	Scale-Invariant Feature Transform
SLAM	Simultaneous Localization and Mapping
SMD	Surface-Mounted Device
SSD	Single Shot Multibox Detector
SURF	Speeded Up Robust Features
SVM	Support Vector Machines
UAVs	Unmanned Aerial Vehicles
UN	United Nations
UV	Ultraviolet
WSN	Wireless Sensor Networks
XPS	Extruded Polystyrene
YOLO	You Only Look Once

Chapter 1

Introduction

1.1 Context

Automation and robotics play a key role in modern agriculture, emerging as a direct response to labour shortages and the need to increase the efficiency and sustainability of agricultural operations [1]. Through the introduction of machines, sensors, and autonomous systems, it is possible to perform repetitive, heavy, and precision tasks more quickly, safely, and with less dependence on human labour, which is increasingly scarce in the agricultural sector. Additionally, these technologies enable more efficient management of natural resources, reducing waste and environmental impacts. The United Nations, through its Sustainable Development Goals (**SDGs**), has set ‘Zero Hunger’, ‘Responsible Consumption and Production’, and ‘Life on Land’ as goals to be achieved by 2030.

The wine sector plays a crucial role in Portugal, both economically and culturally, as well as socially. It is one of the country’s main agricultural activities, contributing significantly to national exports and the development of rural areas, where wine production is often the main economic driver. In addition, Portuguese wine is recognised worldwide for its quality and diversity, reflecting the richness of the territory, climate, and traditions that have been maintained over generations. This sector not only promotes employment and tourism but also preserves iconic landscapes, such as the Douro vineyards, reinforcing Portugal’s identity and prestige on the international stage.

1.2 Motivation

Productivity forecasting is one of the major challenges that producers face, as it is not a one-off measurement and is characterised by significant interannual and spatial variability [2]. As such, the integration of artificial intelligence and automation into productivity forecasting processes makes it possible to anticipate production scenarios and proactively adjust agricultural practices, contributing to more sustainable management and strict compliance with the quality standards imposed by designations of origin.

One of the techniques used to predict productivity in grapevines is bud forcing. This is based on artificially stimulating the budding of dormant vine buds, to predict the plant's development to assess its productive potential. This assessment is based on counting the number of buds that have sprouted and the number of inflorescences per bud, allowing a potential fertility index to be calculated [2]. This index is then used to extrapolate the results of the forcing process to the entire vineyard area. However, this is a time-consuming and demanding procedure, in which manual counting can introduce significant errors, compromising the accuracy of yield forecasts.

1.3 Objectives

The main objective of this dissertation is to contribute to the modernisation, digitalisation, and automation of yield forecasting processes within the viticulture sector. This is achieved through the conceptualisation, design, and practical validation of an automated smart greenhouse specifically optimised for the grapevine bud forcing method. This objective can be divided into the following specific goals:

- Study the data acquisition conditions required for the detection of inflorescences in budding buds;
- Integrate sensing systems to monitor and control the forcing process;
- Study, develop and implement a perception system for the identification and quantification of inflorescences;
- Design, implement and validate a functional prototype of an automated greenhouse for grapevine forcing.

1.4 Contributions

By replacing traditional, labour-intensive, and highly subjective manual counting procedures with an autonomous cyber-physical system, this research aims to provide producers with a reliable, precise, and scalable tool for early productivity estimation. To achieve this, the primary contribution of this work is the creation of the VineComputer prototype, which encompasses the conceptualisation, structural design, and practical assembly of an automated smart greenhouse specifically optimised for the grapevine bud forcing method. This physical development required rigorous hardware development and component selection, including the integration of various subsystems for heating, lighting, ventilation, and irrigation.

Complementing the hardware is the implementation of advanced environmental control algorithms to govern real-time microclimate conditions. Furthermore, this work contributes an edge-computed perception system capable of image stitching and automatic object classification. Finally, as part of the academic dissemination of these advancements, a paper detailing the conceptual framework and initial results of the VineComputer architecture has been submitted to the

ROBOT2026 conference, further contributing to the ongoing discourse in agricultural robotics and automation.

1.5 Document Structure

This document is structured in accordance with the outline presented here.

- Chapter 2 presents the fundamental concepts of precision viticulture and associated monitoring technologies, such as geolocation and remote and proximal detection. It also details the technique of bud forcing as a tool for predicting productivity, exploring the physiology of the vine and the impact of environmental variables, such as temperature, light, water status, and nutrients, on the development of inflorescences.
- Chapter 3 provides a literature review on the state-of-the-art of Controlled Environment Agriculture, smart greenhouses, analysing variable control systems and communication protocols. In addition, it examines the role of computer vision in viticulture, covering image acquisition technologies and object recognition approaches, ranging from classical image processing methods to deep learning techniques, as well as current challenges such as occlusion and environmental variability.
- Chapter 4 outlines the proposed system architecture, conceptualising the VineComputer as an integrated cyber-physical system. It discusses automation and robotics challenges and defines the system's environmental control specifications.
- Chapter 5 addresses the hardware development of the VineComputer platform. It details the physical structure, the design of the environmental subsystems (irrigation, ventilation, heating, and lighting), and the electrical power supply specifications.
- Chapter 6 details the control system and distributed software. It describes the control logic managed by state machines and defines the customised application layer for the CAN communication network between modules.
- Chapter 7 is dedicated to the perception system, explaining the computer vision techniques focused on image stitching and the automatic identification and counting of inflorescences.
- Chapter 8 details the implementation and system integration, covering the physical and structural assembly, the integration of subsystems and cable management, and the practical challenges encountered during development.
- Chapter 9 compiles the experimental tests carried out on the VineComputer to validate its thermal and hygrometric behaviour, along with subsequent analysis.
- Finally, Chapter 10 summarises the main conclusions drawn from the work and presents prospects for future developments.

Chapter 2

Background

This chapter establishes the theoretical foundation necessary to understand the context and technological choices of this dissertation. It provides an overview of precision viticulture and the bud forcing technique, and introduces the supporting technologies that enable modern agricultural automation, including computer vision and communication protocols.

2.1 Overview of Precision Viticulture

Precision viticulture plays a crucial role in maintaining high quality standards in vineyards, especially in a context of increasing competition in global markets. This method allows for optimised agricultural management, responding to the specific needs of each parcel within the vineyard, taking into account the significant variability caused by structural factors, cultivation methods and seasonal weather conditions. The incorporation of new technologies, such as remote and proximal sensors, facilitates the monitoring and management of essential elements of vine growth, including water and nutrient levels, plant health, pest infestations and soil conditions. The use of these tools enables high-resolution mapping of spatial variability in the vineyard, increasing production efficiency, improving grape quality and minimising environmental impact, thus promoting more sustainable and economically viable viticulture [3].

Below are some of the technologies used in precision viticulture, as documented in [3]:

- **Geolocation** - Georeferencing is the process of establishing the relationship between spatial information and its geographical position. This type of Global Positioning System (**GPS**) technology is useful for performing tasks that require high precision, such as crop mapping, automatic farm vehicles, soil sampling, and distribution of fertilisers and pesticides at variable rates.
- **Remote Sensing** - Remote sensing techniques rapidly provide a description of grapevine shape, size, and vigour and allow assessment of the variability within the vineyard. This is image acquisition at a distance with different scales of resolution, able to describe the vineyard. Some examples of remote sensing technologies are:

1. Satellites
2. Aircraft
3. Unmanned Aerial Vehicles (UAVs)

- **Proximal Sensing** - refers to the use of sensors that are close to or in direct contact with the plant or soil to collect detailed data about the vineyard. It is a different approach from remote sensing, which uses data collected from a certain distance. Several key applications of cutting-edge methods in precision viticulture include the close monitoring of:

1. Soil Variability
2. Crop Height and Texture
3. Yield and Quality

2.2 Productivity Forecasting

Productivity forecasting, a key component of precision viticulture, is critically important for the wine industry due to its high sensitivity to discrepancies between expected and actual production. Yield, typically defined as the quantity of harvested grapes per unit surface area, directly affects labour planning, winemaking logistics, market strategy, and even fraud detection [4]. Accurate forecasting depends on maintaining a careful balance between grape production and wine output. In the European Union (EU), regulatory frameworks and quality labels such as Designation of Origin (DO) impose strict maximum yield limits per hectare and define quality standards. Consequently, forecasting productivity for each harvest is essential not only for strategic decision-making within wineries but also as a formal requirement for regulatory bodies across all EU member states.

Estimating productivity remains a complex and uncertain task, as yield can vary significantly between years and across vineyard locations. This variability is driven by multiple interacting factors, including soil and climate conditions, biological and environmental stresses, and the genetic characteristics of the grapevine [2]. Traditional yield estimation methods rely on manual sampling and destructive measurements of yield components, such as the number of bunches per vine, berries per bunch, and average berry weight, but these approaches are labour intensive, time-consuming, and often associated with high error rates, reported to reach approximately 33% in industrial settings [4], [5].

To address these limitations, a wide range of technological solutions has emerged. Computer vision and image processing techniques, using (Red, Green, Blue) (RGB) or depth cameras mounted on autonomous ground vehicles or unmanned aerial vehicles, aim to directly detect and quantify reproductive structures. However, their performance is frequently constrained by fruit occlusion, canopy complexity, and the difficulty of developing models that are robust across grape varieties. In parallel, indirect data-driven approaches exploit vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), to characterise spatial variability in vine vigour,

while aerobiological methods correlate airborne pollen concentrations with regional productivity, enabling yield forecasts up to two months before harvest [4].

More advanced engineering-based solutions include dynamic crop simulation models that integrate climatic, soil, and phenological variables, as well as trellis tension sensing systems that estimate crop mass in real time by monitoring the mechanical load exerted on vineyard support wires [4].

Therefore, the development of reliable technologies capable of predicting vineyard productivity well in advance of harvest is essential. Such tools enable timely management decisions, including yield adjustment and resource allocation, ultimately supporting both economic sustainability and regulatory compliance in modern viticulture.

2.3 Bud Forcing

Bud forcing is a productivity forecasting technique. It involves collecting shoots with dormant buds (Figure 2.1). These buds are then placed in controlled conditions of temperature, humidity, and light to trigger bud break. Fertility is assessed by observing and counting the inflorescences (Figure 2.2). While this method does not consider factors like climate or diseases during the growing cycle, it is known for its ability to provide a representative sample [2]. Additionally, it takes place during the winter before the harvest, enabling early productivity forecasts.

Despite its methodological simplicity, this is a labourious and time-consuming process, which reinforces the need to automate it, making it more efficient and attractive and promoting its widespread adoption.



Figure 2.1: Set of shoots with dormant buds to be subjected to bud forcing.



Figure 2.2: Inflorescences observed during a bud forcing procedure.

2.3.1 Grapevine Bud Physiology and Fruitfulness

Grapevine winter buds are complex compound organs composed of a large primary bud flanked by smaller secondary and tertiary buds [6].

As in most spring-flowering perennials, floral development in grapevine begins during the previous growing season as shown in Figure 2.3, when the primary bud forms meristematic “an-lagen” that differentiate into inflorescence primordia. Following this floral differentiation, buds enter dormancy as hormonal signals suppress further growth [6].

Anatomical studies show that a dormant node typically contains a central primary bud with two lateral buds, although under normal conditions only the primary bud develops into a shoot and produces clusters in spring [6]. A bud is considered fruitful if it contains at least one inflorescence primordium; otherwise, it remains vegetative [6]. Fruitfulness varies with cultivar and node position along the shoot, with basal buds often less fruitful and mid-shoot buds generally showing the highest potential [6].

Environmental conditions during inflorescence formation, particularly light exposure, temperature, and carbohydrate availability, strongly influence the number of primordia formed [6]. Consequently, bud fruitfulness, expressed as the number of inflorescence primordia per bud, provides a primary estimate of yield potential, since each primordium may develop into a grape cluster in the following season [6].

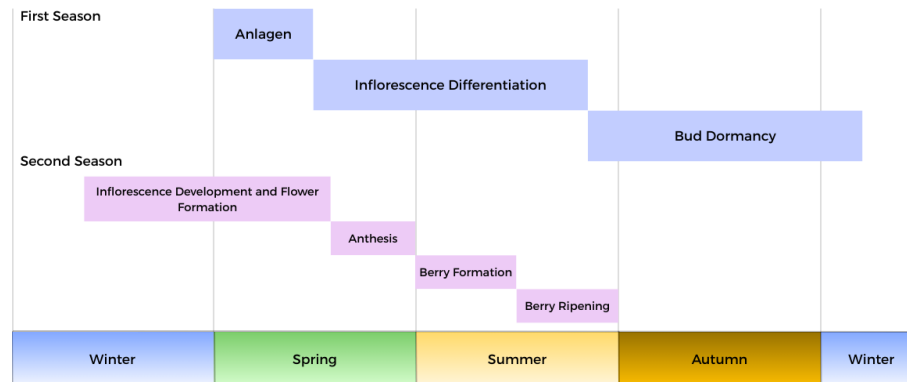


Figure 2.3: Grapevine reproductive cycle.

2.3.2 Climate Conditions

The automation of the bud forcing technique represents a critical step toward scaling its use for ultra-early yield prediction and decision support in viticulture.

Automating this process requires precise control of key environmental variables, namely temperature, relative humidity, photoperiod, and macronutrients availability.

2.3.2.1 Temperature

Temperature is one of the environmental factors that most affects the induction and differentiation of inflorescences in dormant buds [6].

High temperatures favour the formation of inflorescences, with the ideal range for this development being between 20 °C and 35 °C [5], [6]. On the contrary, temperatures below 20 °C promote the formation of tendrils instead of reproductive structures, which reduces bud fertility [5], [6], [7]. Studies indicate that exposure to temperatures above 30 °C for only 4 to 5 hours a day may be sufficient to induce the maximum number of inflorescences [6], [7].

In addition, temperature influences hormonal balance: heat stimulates the biosynthesis of cytokinins (which favour floral differentiation), while cold promotes gibberellins (which favour vegetative growth) [5], [6], [7].

During the budburst process, lower temperatures can, curiously, result in a greater number of flowers per inflorescence by delaying vegetative growth and allowing for a longer differentiation period [5], [7].

2.3.2.2 Light

Light is considered a key factor in the initiation and development of inflorescences in buds. Increased light intensity and direct exposure of branches to solar radiation significantly increase the

number of inflorescence primordia [5], [6]. In contrast, excessive shading (especially a 70% reduction in light intensity) or low light levels drastically reduce fertility and can lead to Primary Bud-Axis Necrosis (PBN) [5], [6], [7].

The importance of light is mainly manifested through photosynthetic activity, which ensures the availability of carbohydrates (energy reserves) necessary for buds to develop complex reproductive structures [5], [6].

The photoperiod (length of day) is generally considered less decisive for floral induction in vines than temperature or light intensity [5], [6], [7]. Although most *Vitis vinifera* varieties appear to be insensitive to photoperiod, there are specific varietal responses: varieties such as Muscat of Alexandria are considered neutral, while Riesling and Shiraz show greater fertility under long-day conditions [5], [6], [7].

In the forcing method under controlled conditions, photoperiod is one of the parameters regulated to break dormancy and ensure uniform bud break [6].

2.3.2.3 Water Status

The water status of the vine influences fertility directly (maintenance of cell turgidity) and indirectly (transport of nutrients and photoassimilates) [6].

Severe water stress reduces photosynthetic activity, which limits the energy available for inflorescence differentiation, resulting in fewer and smaller reproductive structures. In addition, it alters the hormonal balance, decreasing cytokinins and increasing Abscissic Acid (ABA), which inhibits floral development [6].

Interestingly, moderate water stress can increase fertility by reducing canopy density, improving bud exposure to light [5], [6].

Excessive irrigation is cited as one of the factors associated with PBN [6].

2.3.2.4 Macronutrients Availability

A balanced presence of macronutrients is essential for floral induction and differentiation:

- **Nitrogen (N):** It is essential for the synthesis of proteins, chlorophyll, and hormones. If levels are low, the application of nitrogen increases the number of inflorescences and flowers. However, excess nitrogen is harmful, as it excessively increases the vigour of the plant, causing shading of the buds and promoting the synthesis of gibberellins, which inhibit floral differentiation [6].
- **Phosphorus (P):** Intervenes in energy metabolism (as a constituent of nucleic acids and phospholipids). Its deficiency makes reproductive primordia extremely sensitive, compromising their formation and maintenance [6].
- **Potassium (K):** Acts in enzyme activation, photosynthesis, and the plant's water relations. Sources highlight that potassium fertilisation can promote a significant increase (between 40% and 58%) in the size of inflorescence primordia [6].

2.4 Support Technologies

2.4.1 Sensors, Image Acquisition Technologies and Principles of Operation

Data acquisition in viticulture uses a range of sensors and platforms adapted to field conditions. The main technologies and methods include:

- **Environmental Monitoring:** Integrated monitoring of the agricultural environment is based on continuous measurement of the microclimate, soil, water and light radiation, using sensors for temperature, humidity, CO₂, substrate moisture, pH, electrical conductivity and Photosynthetically Active Radiation (PAR). This data set helps prevent heat stress, fungal growth and nutritional imbalances, ensuring optimal conditions for photosynthesis and plant growth [8], [9].
- **Sensors and Cameras:** Standard RGB cameras, thermal cameras and spectral cameras are used. Laser and LiDAR sensors are also used to estimate canopy size and detect missing vines [10].
- **Capture Platforms:** Images can be obtained using portable devices such as smartphones and UAVs to cover large areas quickly, or equipped ground vehicles (e.g., dedicated robots or tractors with cameras) [11], [12], [13].
- **Lighting Conditions:** Capture can take place in natural conditions or in controlled environments. To simplify processing and remove background complexity (sky, soil, other rows), many researchers use artificial lighting at night (flashes or powerful lamps) or artificial backgrounds (black panels) to highlight the fruits or flowers [10].
- **Video Processing:** More recently, the use of RGB video sequences has enabled the development of ‘on-the-go’ counting systems, where objects are detected and tracked across frames to avoid duplicate counts [13].

2.4.2 Computer Vision

Object recognition methods have evolved from classical image processing approaches to advanced deep learning models:

- **Classical Methods:** These are based on the development of task-specific segmentation and feature extraction algorithms [10]. They include colour-based thresholding techniques, edge detection, and shape recognition, such as the Hough transform for detecting circular objects [10]. Algorithms such as the H-Maxima transform are used to identify light reflection patterns on the surface of flowers and berries [10]. Classifiers such as Support Vector Machines (SVM), k-NN and Multilayer Perceptron (MLP) are often used after manual feature extraction [10].

- **Deep Learning:** Currently, Convolutional Neural Networks (**CNN**) represent the state of the art for object classification and detection in agriculture [10]. Popular models such as You Only Look Once (**YOLO**) (v5, v8, v9, v10), Faster R-CNN, and Single Shot Multibox Detector (**SSD**) allow for the detection and localisation of bunches and flowers in complex environments [10], [13], [14]. Instance segmentation models, such as Mask R-CNN, go further by classifying each pixel, allowing overlapping objects to be separated [10].
- **Tracking and 3D Reconstruction:** In videos, tracking techniques such as SiameseNet or K-Shortest Paths (**KSP**) are used to count inflorescences individually [13]. 3D reconstruction (using stereo cameras or structure-from-motion) is used to estimate the volume and weight of clusters, overcoming the limitations of 2D images that vary with distance from the camera [10].

2.4.3 Controller Area Network (CAN) Protocol

The Controller Area Network (**CAN**) protocol is a serial communication protocol designed to enable the rapid, robust and reliable exchange of information between various electronic modules, without the need for a central computer to control the entire network. It was created for automotive applications, but is now also used in industrial systems, medical equipment, heavy machinery and automation in general.

The main idea behind **CAN** is simple: instead of each device communicating directly with all the others via dedicated connections, all nodes are connected to the same bus. Thus, a control unit, a sensor or an actuator can send a message to the network, and all the other nodes ‘listen’ to that communication. Each device decides whether the message is of interest to it or not, based on the message identifier. This greatly reduces the amount of cabling and makes the system more modular and easier to expand.

In **CAN**, communication takes place via messages, rather than device addresses. This is a fundamental aspect. Instead of saying “send to device X”, the sender includes an identifier in the message that describes the type of data, for example ‘engine speed’, ‘pedal position’ or ‘temperature’. All nodes receive the message, but only those programmed to recognise that identifier process it. This model is known as broadcast-based communication. Furthermore, the identifier also defines the message’s priority: the lower the identifier value, the higher the priority for bus access.

The electrical operation of **CAN** is typically based on two signal wires, called CAN High and CAN Low, which carry a differential signal. Instead of measuring the voltage of each wire relative to ground, the receivers analyse the difference between the two. This technique increases immunity to electromagnetic noise, which is essential in environments with motors, long cables and electrical interference. For this reason, **CAN** is considered a very robust protocol.

A key feature of **CAN** is its method of bus access. As several nodes may wish to transmit at the same time, the protocol uses a non-destructive arbitration mechanism. During the transmission of the identifier, each node compares what it is sending with what it is reading from the bus. If a node

detects that another has higher priority, it stops transmitting and waits for the next opportunity, without corrupting the winning message. This is possible thanks to the way dominant and recessive bits function on the bus. The result is deterministic communication, which is very useful in real-time control systems.

Transmission over **CAN** is organised into frames, which include several fields. Among the most important elements are the identifier, which indicates the message's content and priority, and the data field, which carries the useful information. The classic **CAN** format allows for up to 8 bytes of data per message. The frame structure is illustrated in Figure 2.4.

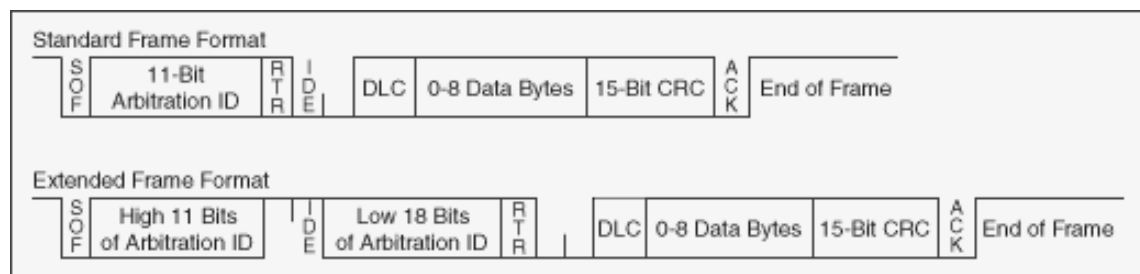


Figure 2.4: CAN frame ¹.

¹<https://www.ni.com/>

Chapter 3

State-of-the-art

This chapter reviews the current literature and existing technological solutions relevant to the project. It explores advancements in Controlled Environment Agriculture (CEA) and analyses computer vision systems applied to viticulture, highlighting their current limitations and open challenges.

3.1 Controlled Environment Agriculture

CEA is a technological response to the growing need to increase the efficiency, resilience, and sustainability of agri-food production [9], [15]. Unlike open-field agriculture, where crop growth is largely dependent on external environmental conditions and limited human intervention, CEA is based on enclosed and highly controlled systems in which key variables, such as temperature, humidity, light, CO₂ concentration, and nutrient supply, are precisely managed to optimise plant growth, yield, and quality, independent of climate or geography [15], [16].

Originally developed from small-scale horticultural and greenhouse practices, CEA has evolved into a large-scale industrial paradigm, giving rise to highly automated plant factories [15]. These facilities enable continuous, year-round production, often in non-arable areas or regions with adverse climatic conditions [15]. Most modern CEA systems rely on soilless cultivation techniques, including hydroponics, aeroponics, and aquaponics, which deliver water and nutrients directly to plant roots, significantly improving resource-use efficiency and productivity.

The contemporary CEA model is closely aligned with the principles of Agriculture 4.0, transforming food production into a data-driven industry [15]. Advanced climate-control infrastructure, such as Heating, Ventilation and Air Conditioning (HVAC) systems, pumps, fans, and Light-Emitting Diode (LED) grow lights, is integrated with dense sensor networks that monitor environmental and plant parameters in real time. These sensors feed Internet of Things (IoT) based control platforms that automate irrigation, fertilisation, ventilation, and lighting. In addition, artificial intelligence and Machine Learning techniques analyse large data streams to optimise control setpoints, predict plant needs, and continuously improve operational efficiency. Together, these technologies position CEA as a key contributor to sustainable agriculture and global food security.

3.1.1 Overview of Smart Greenhouses

Smart greenhouses represent the practical application of **CEA**, integrating network infrastructure, sensors, and actuators to monitor and regulate the microclimate [8].

On the market, smart greenhouse and controlled environment farming systems span a wide spectrum, ranging from simplified consumer kits, such as AeroGarden, a low-cost solution aimed at domestic users that operates as a closed, proprietary platform with limited customisability and no adaptive environmental control, to high performance scientific growth chambers, such as the Conviron A1000, which provide highly precise control over environmental variables, including light, temperature, humidity, and CO₂, but at very high cost and within closed, proprietary platforms [9]. Intermediate solutions include systems such as Leaf, designed for medicinal and cannabis cultivation with active environmental control but limited flexibility due to closed hardware and software, Grove, an aquaponics based platform that integrates nutrient cycling from fish but without a sealed chamber, limiting effective microclimate regulation despite its high price point, and the FarmBot, an open-source Computer Numerical Control (**CNC**) based outdoor farming system that offers high customisability for automated agricultural operations but is fully exposed to ambient weather conditions, preventing environmental control [9].

As an alternative, open source projects such as the Personal Food Computer (**PFC**) (Figure 3.1) are emerging, promoting the sharing of ‘climate recipes’ (sequences of environmental variable set points) among a global community of users and researchers [9]. Table 3.1 presents a comparative analysis of existing commercial farming systems, highlighting their key characteristics, target users, and customisability levels.

Table 3.1: Comparison of Commercial Farming Systems [9]

Characteristics	FarmBot	AeroGarden	Leaf	Grove	Conviron A1000	PFC
Target consumer	Consumer	Consumer	Consumer	Consumer	Scientist	Consumer
Price	\$3100	\$99–\$379	\$1500	\$4500	On request	\$3000
Platform	Open	Closed	Closed	Closed	Closed	Open
Adaptive Environment	No	No	Controlled	No	Controlled	Controlled
Customisability	High	Low	Low	Low	Low	High

The state of the art in this area highlights the transition from traditionally wired systems to wireless and hybrid solutions. Historically, data transfer in greenhouses depended on wired systems, such as fieldbus or **CAN** protocol, known for their robustness but limited by physical rigidity and maintenance costs [16].

Currently, Wireless Sensor Networks (**WSN**) have become predominant due to their flexibility and low installation cost [17]. Protocols such as ZigBee are widely recommended for their low power consumption, network self-healing capabilities, and suitability for environmental monitoring [17]. More recently, the integration of **IoT** technologies has enabled the use of protocols such as 6LoWPAN and RPL, designed specifically for low-power and low-data-loss networks, facilitating centralised management on local servers or in the cloud [15].

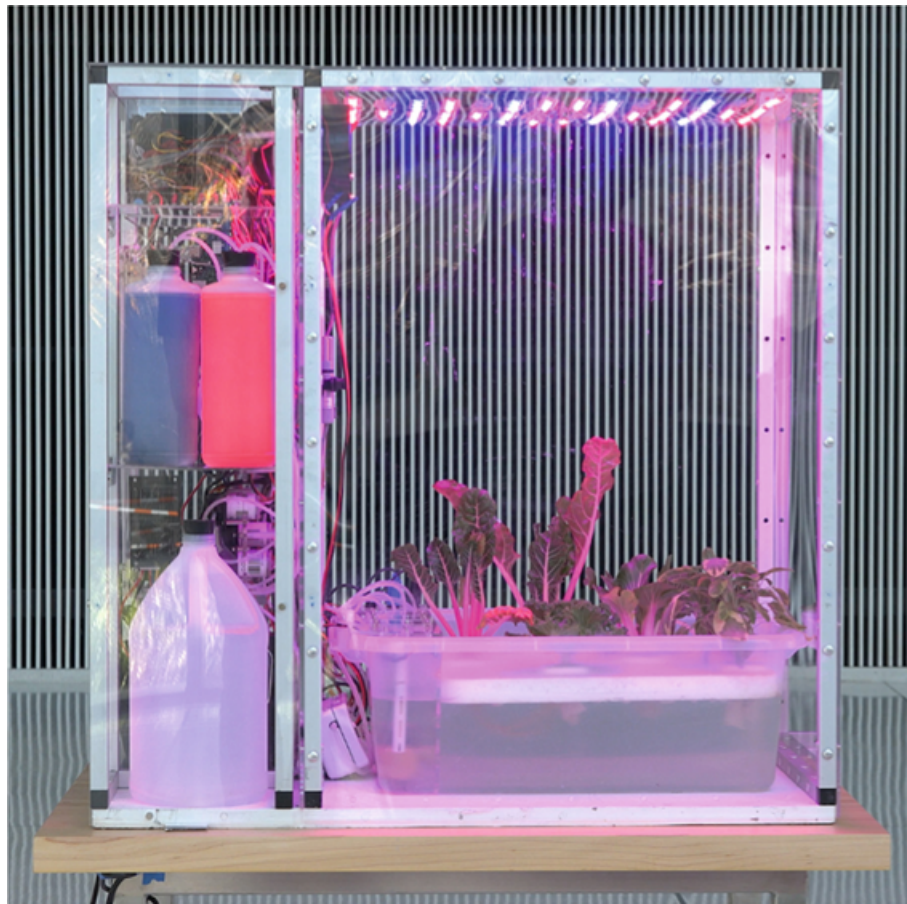


Figure 3.1: OpenAg™ Personal Food Computer (PFC) v2 [9].

3.1.2 Automation and Climate Conditions Control

The control of environmental variables in smart greenhouses is achieved through a sophisticated integration of sensors, decision algorithms and actuators. This cycle allows plants to be treated as ‘robotic agents’ in an Agricultural Cyber-Physical System [9].

The following section details the controlled variables and the methods employed for their regulation:

- **Air Temperature and Humidity:** These are critical variables, as extreme conditions can lead to plant stress, disease development, or death, while suboptimal levels can impair growth and overall health [16]. Control is achieved using sensors such as the AM2315 or DHT22 [8], [9]. To operate, Positive Temperature Coefficient (PTC) heaters, cooling units, fans, and humidifiers are used [16].
- **CO₂ concentration:** Monitored to maximise photosynthesis, for example, using infrared sensors such as the MH-Z16 [8], [9]. Control is performed by solenoid or motorised valves that manage the gas dosage in the growth chamber [9].

- **pH and Electrical Conductivity (EC):** pH indicates the level of acidity and EC reflects the concentration of dissolved nutrients [8]. Control is automated through peristaltic pumps that inject precise amounts of ‘pH Up’, ‘pH Down’ and liquid nutrient solutions [9].
- **Soil Moisture and Oxygenation:** Resistance sensors measure the water content in the soil to activate irrigation pumps [18]. In hydroponic systems, aerators and stones are used to increase the oxygen dissolved in the water, preventing root diseases [9].
- **Luminosity:** Lighting control is achieved through Pulse Width Modulation (PWM), allowing the intensity of the LED to be adjusted without altering their chromaticity [15]. Lighting is distributed through independent spectral channels (red, blue, and white) to ensure adequate PAR [9], [15], and may additionally include controlled exposure to Far-Red (to stimulate stem elongation) and Ultraviolet (UV) (to stimulate chemical compounds such as flavonoids), carefully regulated in intensity and duration to avoid stress on the plants [15].

Environmental variables are controlled through a combination of dynamic control strategies, hardware abstraction, and advanced algorithms. Rather than relying on static set points, these types of systems use ‘climate recipes’ that specify time-based sequences of target values, such as automatically reducing temperature after a defined period [9].

Control is implemented in a hardware-agnostic manner, whereby the software issues logical, high-level commands (e.g., dispensing a specific volume) instead of direct actuator instructions, ensuring that the same control logic can be deployed across different greenhouses with different hardware configurations [9].

To manage uncertainty and optimise performance, advanced algorithms are employed, including Fuzzy Logic for smooth parameter transitions, numerical methods such as Newton’s method for iterative adjustment of variables like lighting intensity, and, in large-scale installations and Reinforcement Learning models that dynamically regulate systems such as HVAC to minimise energy consumption while maintaining optimal environmental conditions [8], [15].

3.2 Computer Vision in Viticulture

Computer Vision (CV) refers to algorithms designed to extract meaningful knowledge and information from images or videos [10]. In precision viticulture, this technology is applied to manage plot heterogeneity, allowing for finer control over crop yields, early disease detection, and the production of higher quality fruit [10]. Traditionally, tasks such as counting berries and grapes to estimate harvests or inspecting vines are performed manually, which makes them time-consuming, costly and prone to human error due to fatigue or lack of uniform training [10], [14].

The automation of these tasks through computer vision allows large amounts of data to be processed, assisting winegrowers in crucial decisions such as harvest organisation and the selection of high-quality grapes [10]. The application of this technology spans multiple stages of crop development, from the early detection and prediction of inflorescence and flower emergence (Figure 3.2)

to the monitoring of fruit ripening and the estimation of final grape yield and weight [10]. In addition to productivity, CV is used for selective pesticide spraying, automated pruning in winter, and large-scale phenotyping [10].

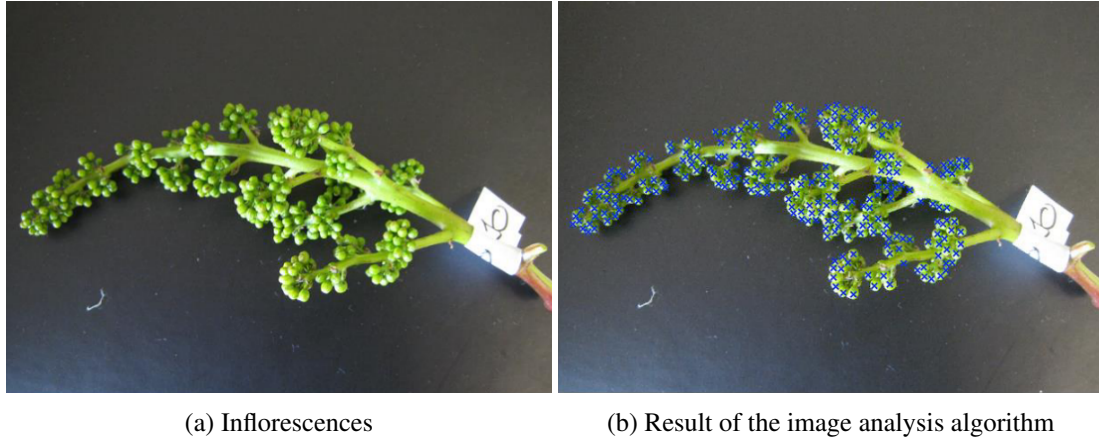


Figure 3.2: Demonstration of the image analysis algorithm vitisFlower® for automatically detecting flowers. [11]

3.2.1 Object Recognition Methods

Object recognition constitutes a central component of vision-based systems for flower and inflorescence detection in viticulture, as it directly influences the accuracy of yield estimation and phenological assessment. Over time, a wide range of approaches has been explored, evolving from classical computer vision techniques based on handcrafted features to advanced Deep Learning models capable of learning complex visual representations from data. These methods differ significantly in terms of detection accuracy, robustness to environmental variability, computational requirements, and suitability for deployment in real-world vineyard conditions. This section reviews the main object recognition strategies reported in the literature, categorising them into classic computer vision methods, Deep Learning-based approaches, and techniques that incorporate video tracking and three-dimensional reconstruction.

3.2.1.1 Classic Methods of Computer Vision

- **H-Maxima Transform:** It is based on the pattern of light reflection on the circular surface of flower buds [10]. Algorithms such as the h-maxima transform identify local brightness maxima to count individual flowers. This technique is the basis of the vitisFlower® application [10], [11], [14].
- **Hough Transform and SURF:** Other approaches use the Circular Hough Transform to detect spherical shapes or feature descriptors such as Speeded Up Robust Features (SURF) to filter flower candidates after canopy segmentation [10], [14].

- **Watershed Algorithm:** It uses image topography to separate adjacent objects. Recently, an iterative watershed method was proposed that automatically adjusts markers to segment flowers of different sizes and densities [14].

3.2.1.2 Deep Learning

- **YOLO Family:** From versions v5 to v11, these models have demonstrated excellent accuracy in locating inflorescences. YOLOv8n excelled in detecting individual flowers (F1-score = 91.4%), while YOLOv11 proved effective in early detection (pre-flowering), especially under artificial night lighting (F1 = 0.71) [14], [19].
- **RetinaNet and SSD:** RetinaNet is used to detect inflorescences in videos, using an architecture that balances location accuracy with processing speed [13]. SSD has also been applied for detection at different stages of growth.
- **Mask R-CNN:** It is the reference for instance segmentation. Often, a two-step approach is used: first, the network segments the inflorescence, and in a second step, it detects and quantifies each individual flower within that area. This method outperformed algorithms such as Hough Transform and SegNet in terms of counting accuracy [20].
- **Fully Convolutional Network (FCN), SegNet and U-Net:** Semantic segmentation models such as this have been applied to extract canopy features and locate vegetative organs in unstructured conditions [14], [20].

3.2.1.3 Video Tracking and 3D Reconstruction

- **KSP and SiameseNet:** In RGB video sequences, algorithms such as KSP and SiameseNet networks allow detections to be associated between consecutive frames, ensuring that each inflorescence is counted only once [13].
- **3D Reconstruction and Simultaneous Localization and Mapping (SLAM):** Methods based on stereo cameras or SLAM algorithms are explored to estimate flower volume and overcome occlusions, although they require high computational capacity [10].

3.2.2 Limitations and Open Challenges in Vision-Based Systems

Despite significant technological advances, the application of computer vision in viticulture still faces several challenges that hinder its full commercial deployment.

One of the most critical limitations is occlusion, as dense foliage often conceals a substantial portion of grape clusters and flowers. In some grape varieties, leaves can obscure up to 72% of the fruit, severely impacting yield estimation accuracy [10].

Environmental variability further complicates visual analysis, since changing natural lighting conditions, such as shadows and direct sunlight, combined with complex backgrounds make robust

image segmentation difficult [10], [21]. Additionally, wind-induced plant movement can degrade image sharpness and reduce the reliability of three-dimensional tracking [10], [21].

Another major challenge is colour confusion, particularly during early phenological stages, when flowers and immature berries exhibit strong chromatic similarity to surrounding foliage, making accurate visual discrimination extremely difficult [10], [14], [22].

The lack of large, high-quality annotated datasets also represents a significant bottleneck, as training Deep Learning models requires thousands of images manually labelled by domain experts, a process that is both time-consuming and labour-intensive [10], [14].

Furthermore, model generalisation remains limited, with many approaches being developed for specific grape varieties, locations, or phenological stages, and therefore performing poorly when exposed to different cultivars, environments, or seasonal conditions [10], [14], [23].

Finally, the computational demands of advanced computer vision and Deep Learning models often require powerful hardware, such as Graphics Processing Unit (GPU), which can impede their integration into mobile devices or autonomous field robots with constrained processing and energy resources [10], [14].

Chapter 4

Proposed System Architecture

This chapter presents the high-level conceptualisation of the VineComputer platform. It delineates the integrated cyber-physical architecture designed to automate the bud forcing technique, outlining the primary automation challenges and the strict environmental control specifications required for the system.

4.1 System Architecture Overview

The VineComputer platform is conceptualised as an integrated cyber-physical system designed to automate the traditional, manual grapevine bud forcing process within a modular and highly controlled environment. The structural and logical configuration of the system is organised around a distributed processing topology that ensures environmental control and autonomous data acquisition. At a high level, the system architecture consists of a central processing and perception layer, a localised microclimate monitoring node, an electronic power interface module, and a series of dedicated environmental actuators. The core computational hub is governed by the MOXOH platform, which handles high-level system coordination and executes deep learning models for inflorescence detection. This central unit operates in tandem with a specialised Weather Station node, responsible for real-time sensory data collection, and the AgIoT4Power module, which regulates the physical power delivery to the environmental hardware.

Rather than relying on a centralised computing framework, these distinct nodes are interconnected via a **CAN** bus protocol. This communication bus enables robust, differential, and deterministic message broadcasting across the system while drastically reducing internal wiring complexity. The distributed software architecture relies on an event-driven paradigm managed by non-blocking state machines running on a microcontroller. This asynchronous operational cycle continuously updates the global system context, executing microclimate adjustments and image capture tasks within a cooperative polling framework. This high-level structural framework and the proposed architecture can be seen in Figure 4.1, providing the necessary foundation and overview for the specifications detailed in the subsequent chapters.

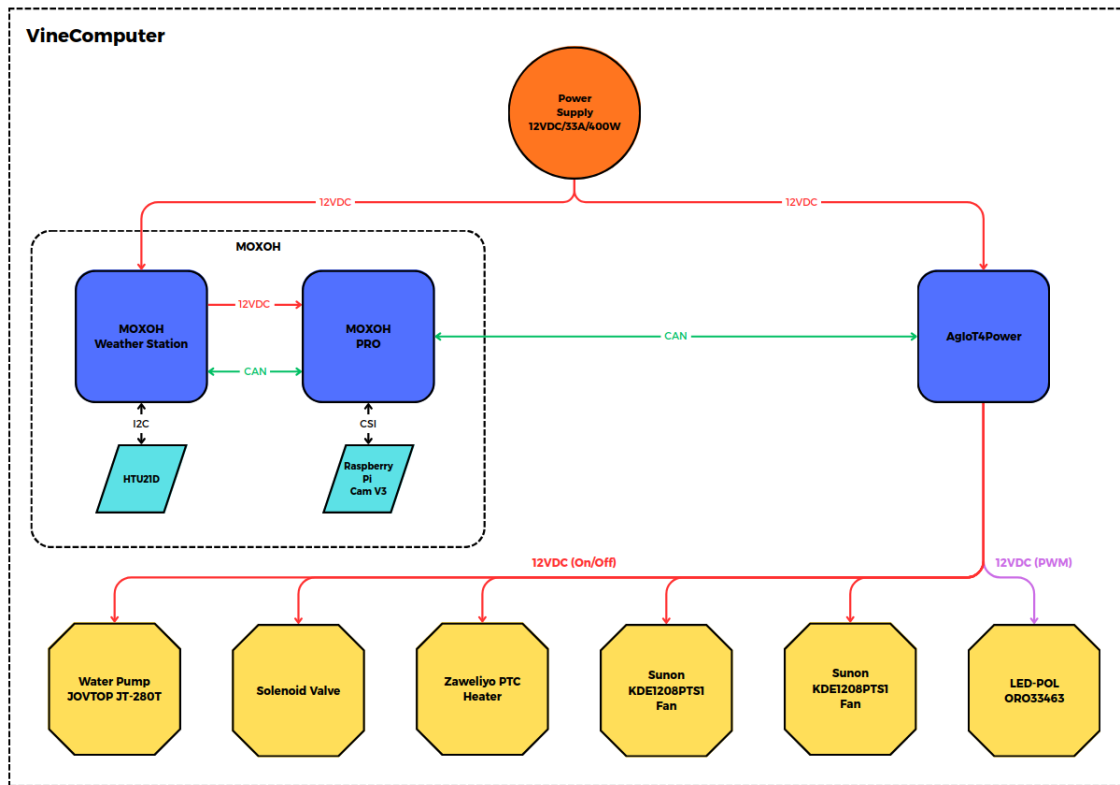


Figure 4.1: High-level system architecture diagram of VineComputer, depicting the interconnection between the different modules and actuators.

4.2 Automation and Robotics Challenges

Implementing an automated cyber-physical system for Controlled Environment Agriculture (CEA) within the viticulture sector introduces a series of distinct engineering, structural, and biological challenges. From an automation and control perspective, a primary difficulty lies in the mitigation of high natural environmental variability to achieve reproducible experimental conditions, which is essential for eliminating the subjective discrepancies and high error rates inherent to traditional manual methods.

Biologically, the system must accommodate strict plant health constraints, specifically regarding the precise humidification of the substrate without wetting the aerial parts of the plant. Because prolonged exposure of vegetative tissues to moisture promotes the proliferation of destructive fungal pathogens, the automation strategy requires a targeted hydraulic design that strictly isolates root-zone hydration from above-ground structures.

Structurally and thermodynamically, the physical architecture demands the complete isolation of the growth chamber, purposefully avoiding any unsealed openings to the outside environment. This strict containment is critical not only to prevent uncontrolled air exchange but also to guarantee high energy efficiency by minimising thermal losses and maintaining a stable microclimate.

4.3 System Requirements

The operational capabilities and structural boundaries of the VineComputer platform are defined by a set of engineering requirements.

The VineComputer must:

- Autonomously monitor and regulate the internal microclimate maintaining air temperature within $\pm 1^\circ\text{C}$ and relative humidity within $\pm 5\%$ of the defined points;
- Simulate a photoperiod cycle with adjustable light intensity and duration;
- Autonomously irrigate the cultivation area, ensuring that the root zone is uniformly hydrated based on substrate moisture parameters;
- Capture high resolution stereo images of the cultivation area at predefined time intervals;
- Efficiently stimulate the sprouting of dormant buds through controlled environmental conditions;
- Identify and quantify emerging inflorescences.

4.3.1 Environmental Control Specifications

To meet the stipulated requirements, the environmental parameters within the growth chamber are continuously managed through specific loops. The operational relationships between the controlled environmental variables, their corresponding monitoring sensors, the associated physical actuators, and the overarching agronomic objectives are systematically outlined in Table 4.1.

Table 4.1: Controlled variables.

Variable	Sensor	Actuator	Objective
Temperature	HTU21D	Zaweliyo 180W PTC Heater	Maintain an optimal internal set-point of 25°C via a hysteresis control algorithm
Relative Humidity	HTU21D	2 Sunon KDE1208PTS1	Maintain the internal relative humidity near a target of 75% via hysteresis control
Light Intensity	None	LED-POL ORO33463	Replicate a 12-hour spring photoperiod
Substrate Moisture	None	JOVTOP JT-280T & Solenoid Valve	Humidify the substrate

Chapter 5

VineComputer

Building upon the architectural requirements, this chapter details the physical and electronic hardware development of the VineComputer. It provides a comprehensive breakdown of the structural design, the selection and integration of critical subsystems and the configuration of the power supply network.

5.1 Hardware Development

Structure and Dimensions

The design of the greenhouse structure began with the determination of its dimensions, taking as a starting point the tray currently used in the forcing technique, measuring $60.5 \times 40.6 \times 5.5$ cm. Based on this reference, it was concluded that the climate-controlled chamber would need to accommodate this tray with some extra space, ensuring sufficient room for its placement and handling, resulting in a length of 80 cm and a width of 50 cm.

To determine the height, a calculation was carried out, based on the diagram in the Figure 5.1, to establish the minimum height at which the cameras would need to be positioned in order to capture the entire tray.

The projection geometry of each individual camera determines the width of the area captured on the floor (L_{cam}) as a function of the height (H) and the Field of View (FOV), in accordance with the basic trigonometric relationship:

$$L_{cam} = 2 \cdot H \cdot \tan\left(\frac{FOV}{2}\right) \quad (5.1)$$

When combined in parallel, the total width of the illuminated area covered by both cameras (L) extends beyond the field of view of a single camera due to the physical offset (B). Thus, the total combined width is given by:

$$L = \frac{L_{cam}}{2} + \frac{L_{cam}}{2} + B = L_{cam} + B \quad (5.2)$$

By combining the two equations (5.1 and 5.2) and isolating the height variable (H), we obtain the function that determines the height required to cover a given total length (L):

$$H(L) = \frac{L - B}{2 \cdot \tan(\frac{FOV}{2})} \quad (5.3)$$

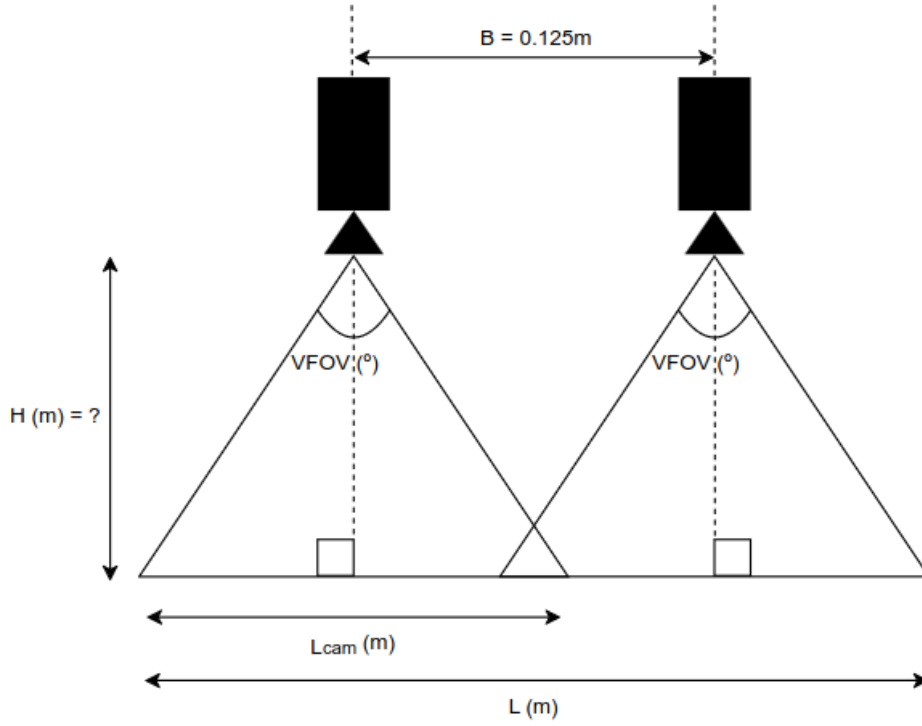


Figure 5.1: Geometric schematic of the MOXOH dual-camera configuration used to determine the minimum mounting height above the propagation tray.

Given the physical layout of the cameras on the Printed Circuit Board (PCB), the MOXOH was positioned to align the widest field of view of the cameras, in this case the horizontal field of view ($HFOV = 66^{\circ}$), with the longest dimension of the tray (which is 0,605 m in length). Consequently, the vertical field of view ($VFOV = 41^{\circ}$) was oriented along the width of the board (0,406 m).

Substituting the value $B = 0,125 \text{ m}$ and the corresponding values for L and FOV into equation 5.3 yields the following height values:

- Calculation for the length axis of the tray:

$$H(L) = \frac{0,605 - 0,125}{2 \cdot \tan(\frac{66}{2})} \approx 0,3695 \quad (5.4)$$

- Calculation for the width axis of the tray:

$$H(L) = \frac{0,406 - 0,125}{2 \cdot \tan(\frac{41}{2})} \approx 0,3758 \quad (5.5)$$

This calculation resulted in an approximate minimum height of 37,6 cm between the cameras and the tray. Based on these criteria, it was decided that the climate-controlled chamber would measure $80 \times 50 \times 50$ cm to accommodate all components with sufficient space.

Once the dimensions of the climate chamber had been finalised, a compartment was added to house the electronics and the water tank, the latter being smaller in size, measuring approximately $20 \times 50 \times 50$ cm. In order to mitigate the risks associated with the vulnerability of electronic components to moisture, it was decided to physically separate the two compartments, a solution that enhances the overall robustness of the prototype. Another advantage inherent in this design lies in the ability to refill the water reservoir without interrupting the insulation regime of the climate-controlled chamber, minimising the frequency of opening and preserving the integrity of the internal microclimate.

Materials

Following the definition of the system's dimensions, the development focused on the selection of materials and structural design, guided by four core requirements: portability, robustness, aesthetics, and functionality. To achieve high structural strength while minimising overall weight, aluminium was selected as the primary material for the structure.

Two distinct aluminium configurations were evaluated: technical profiles (T-slot type) and conventional profiles. The selection fell upon 30×30 mm technical profiles due to their high modularity, the extensive variety of compatible market accessories, and ease of assembly, as exemplified by the T-slot profile geometry illustrated in Figure 5.2. Furthermore, this profile geometry significantly facilitated the fastening of the insulation material, which proved to be a major advantage during the system integration phase.

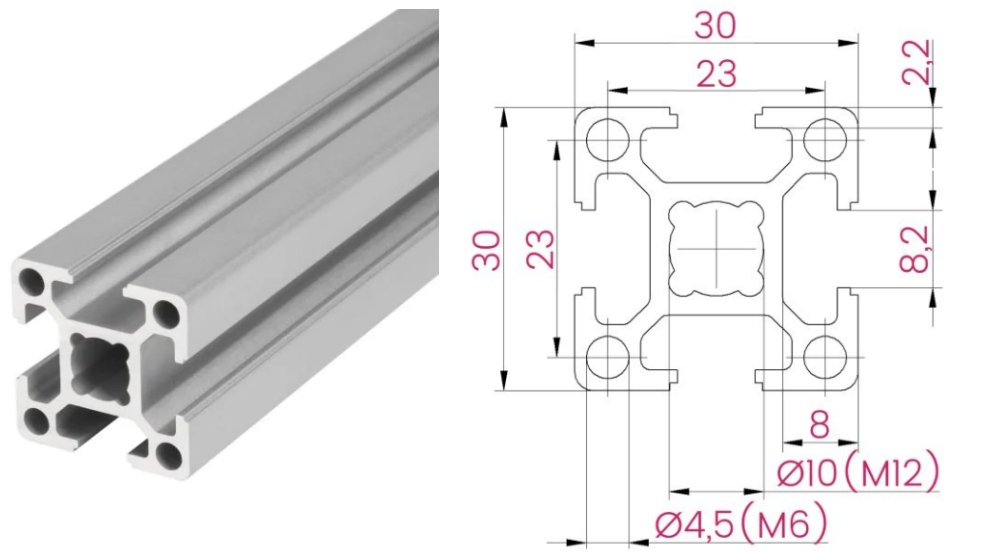


Figure 5.2: 30 × 30 mm T-slot aluminium structural profile with four slots, showing the cross-sectional geometry and mounting hole dimensions. ².

Regarding the thermal insulation of the climate chamber, various material solutions were evaluated, namely Extruded Polystyrene (XPS), Expanded Polystyrene (EPS), rock wool and multi-wall polycarbonate. Among the alternatives analysed, XPS demonstrated the highest thermal performance, in contrast to EPS, which recorded the least favourable results. Notwithstanding the thermal superiority of XPS, the solution selected for the structural walls of the greenhouse was multi-wall polycarbonate. This choice was justified by the excellent balance this material offers between insulation capacity, mechanical strength, lightness and ease of procurement. Additionally, its commercial availability in an 8 mm thickness proved ideal, as it significantly simplified the fitting and direct assembly into the slots of the aluminium technical profiles, as shown in Figure 5.3. In order to enable continuous visual monitoring of the interior of the greenhouse without compromising the microclimate, the two front faces, corresponding to the access doors, were clad with transparent acrylic panels.

²<https://reiman.pt/pt/>

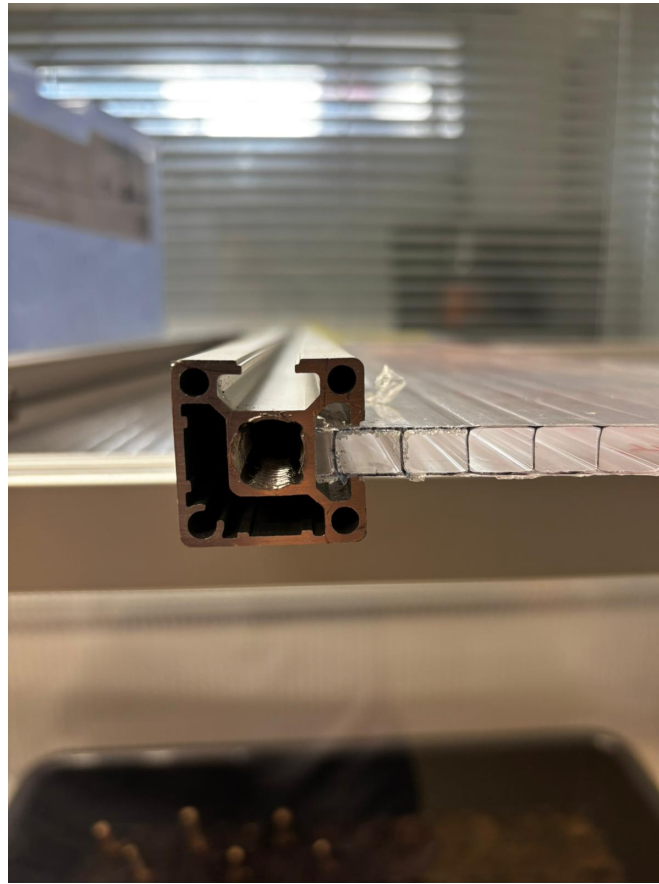


Figure 5.3: Detail of a multi-wall polycarbonate panel assembled directly into the slot of a 30×30 mm aluminium T-slot profile.

In short, this set of design decisions made it possible to create a perfectly balanced structure. The final design combines an optimised geometry for the image acquisition system, a robust and modular architecture, and a selection of materials that is fully compatible with the system's operational requirements.

In order to validate the correct integration of all subsystems and mitigate potential mechanical interference errors, a complete three-dimensional model (Figure 5.4) of the greenhouse assembly was developed using Autodesk Fusion Computer-Aided Design (CAD) software. This virtual approach establishes a flexible foundation that significantly simplifies the design and future prototyping of new parts or customised accessories that may be implemented in the system.

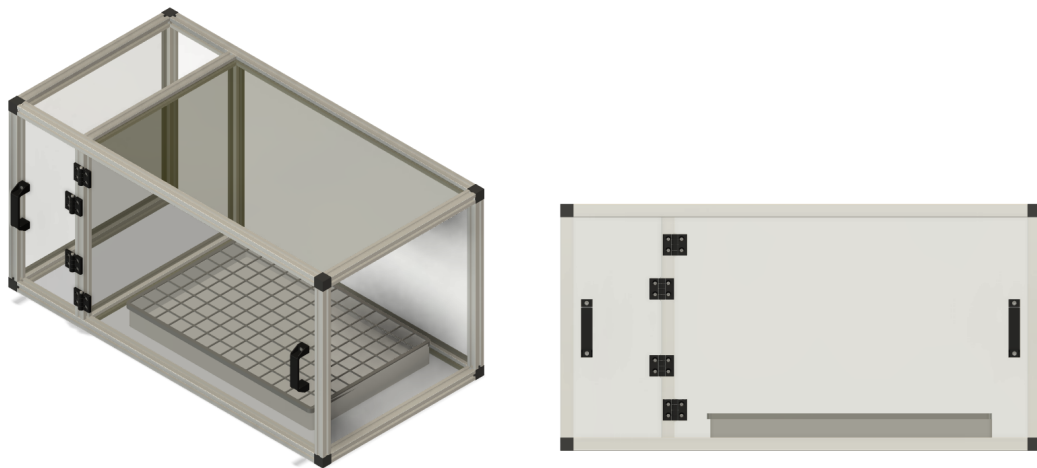


Figure 5.4: Three-dimensional CAD model of the VineComputer developed in Autodesk Fusion.

Control Units

MOXOH

MOXOH is an autonomous environmental and biodiversity monitoring platform developed to support decision-making systems through the collection, processing and transmission of real-time data. Its design is based on three fundamental principles: economic viability, interoperability and cross-domain applicability across different health and environmental sectors. These principles enable the platform to be used in a variety of monitoring scenarios, ranging from the epidemiological surveillance of disease-carrying insects to the monitoring of agricultural pests and environmental parameters.

The MOXOH architecture integrates various hardware subsystems that work in coordination to gather relevant information from the surrounding environment. These include the camera system, computational processing modules, environmental sensor systems, remote communication mechanisms and autonomous energy management.

One of the platform's core features is its advanced high-resolution imaging system, which is equipped with autofocus mechanisms and fully optimised for continuous observation. This setup captures high-quality visual data capable of effectively supporting computer vision algorithms and machine learning models tailored for the detection, identification, and classification of observed organisms.

To handle this data efficiently, MOXOH shifts away from traditional approaches that rely entirely on external servers for data processing. Instead, it leverages edge computing by performing computational tasks locally, directly at the data acquisition source. This on-device processing significantly reduces latency and minimises the bandwidth required for data transmission. Consequently, it enables the seamless deployment of artificial intelligence techniques for real-time image analysis, allowing the data to pass through consecutive stages such as pre-processing, segmentation, object detection, feature extraction, and automatic classification.

While these capabilities are currently applied to identify and count insect species within the context of biodiversity monitoring, MOXOH's computational framework is highly versatile. It is not constrained to this specific field and can be adapted to any real-world application that requires automated image acquisition and processing.

At the same time, the platform incorporates a set of environmental sensors capable of monitoring variables such as temperature, relative humidity, solar radiation and precipitation. The combination of visual information and environmental parameters enables the development of more robust predictive models, allowing the presence of certain species or biological phenomena to be correlated with the observed environmental conditions.

In addition, MOXOH is designed to operate autonomously for long periods, using power systems based on batteries and solar panels. This feature makes it possible to install the system in remote or hard-to-reach locations, significantly reducing the need for human intervention and the operational costs associated with monitoring campaigns.

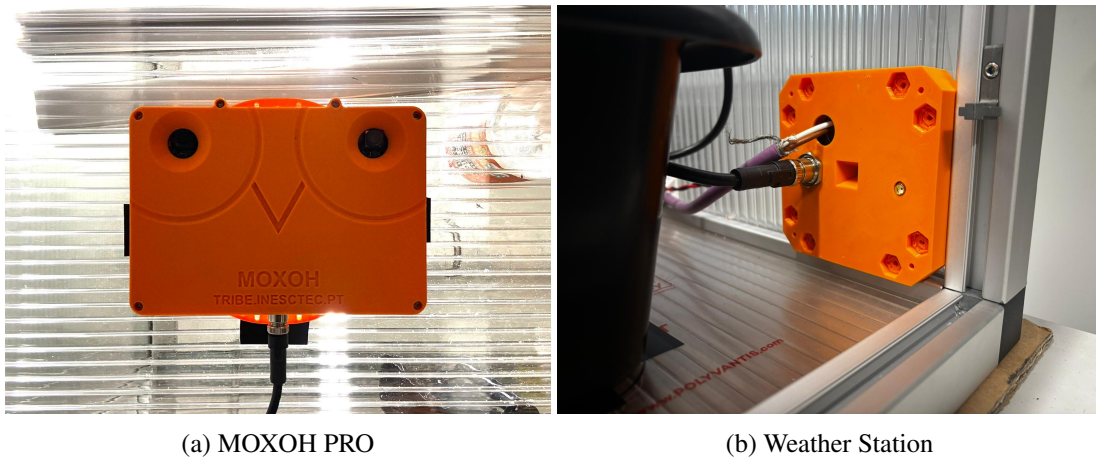


Figure 5.5: MOXOH system components installed in VineComputer.

In the VineComputer architecture, the MOXOH platform serves as the central processing unit and operational core. Although originally developed for biodiversity monitoring, its robust edge computing capabilities, high-resolution imaging, and seamless sensor integration make it highly adaptable for automated viticulture. By consolidating all major computational tasks into a single edge device, MOXOH acts as the system's 'brain', driving three fundamental operations simultaneously. Firstly, it continuously collects and processes critical microclimatic data, specifically air temperature and relative humidity, which dictate the system's automated decision-making. Secondly, it manages the periodic image acquisition of the developing vine shoots and locally executes the artificial intelligence algorithms required to automatically identify and count inflorescences, delivering immediate indicators of yield potential. Finally, the platform runs the overarching decision logic, directly translating real-time sensor telemetry into specific commands for the greenhouse actuators to autonomously regulate the growing environment.

AgIoT4Power

AgIoT4Power (Figure 5.6) serves as the system's power interface module, establishing the connection between the MOXOH control and supervision unit and the various actuators installed on the VineComputer. Its main function is to receive high-level commands from the control network, process them locally and convert these commands into electrical signals capable of powering and controlling power loads, namely the ventilation fans, the PTC heaters, the water pump, the solenoid valve and the LED strips.

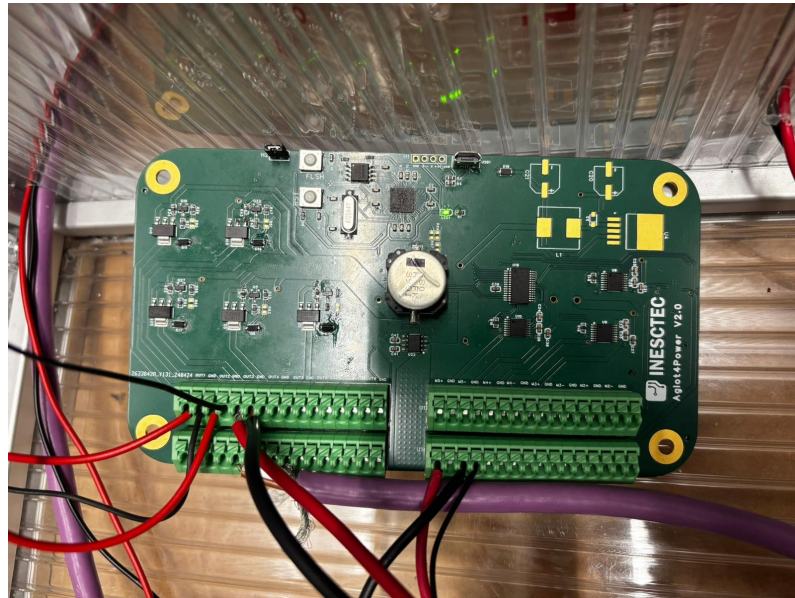


Figure 5.6: AgIoT4Power board installed in the VineComputer for power interface between the control unit and the actuators.

The AgIoT4Power architecture is organised into four main functional blocks:

- **Power supply system:** The board is powered by a DC input voltage (+VIN) from the power supply, corresponding to the voltage used by the actuators (12 V Direct Current (DC)). This voltage is used to generate the various supply voltages required by the internal electronic circuits.

The primary conversion is carried out by a buck converter, which generates the 5 V supply. Subsequently, another buck converter produces the stabilised 3.3 V supply used by the microcontroller, the CAN transceiver and the other digital circuits of the board. This architecture ensures a stable power supply to the control circuits, regardless of load variations introduced by the actuators, contributing to the overall robustness of the system.

- **CAN communication system:** Communication between MOXOH and AgIoT4Power takes place via CAN. The physical CAN interface is implemented using a transceiver, which is responsible for converting between the RP2040's logic levels and the CANH/CANL differential bus.

From a functional perspective, MOXOH sends **CAN** messages containing actuation commands. AgIoT4Power receives these messages, interprets the associated identifiers and parameters, and executes the corresponding actions on the various actuators.

- **Processing and control system:** Like the MOXOH, the board's computational core is based on the Raspberry Pi RP2040 microcontroller, which is responsible for running the firmware, managing communications and controlling the actuators by activating their GPIO pins.
- **Power drive system:** The AgIoT4Power provides ten high-side switches, like the one shown in Figure 5.7, to power the output channels, labelled OUT1+ to OUT10+, implemented using P-channel MOSFETs driven by driver stages comprising bipolar transistors. These switches are used to enable the RP2040's low-voltage and low-current pins to control higher-power loads.

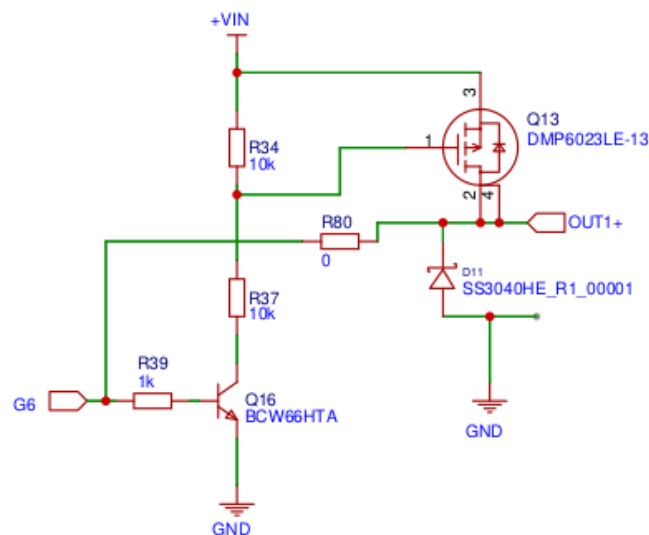


Figure 5.7: Schematic of a single high-side switch channel on the AgIoT4Power board.

The operation of the actuators is based on the alternation between two logic states controlled by the RP2040's GPIO pins, which determine whether or not the actuator connected to OUT+ receives power. Below is a detailed explanation of how this switch works, using the one shown in Figure 5.7 as an example:

When the actuator is intended to be turned off, the RP2040 sets the G6 pin to a low logic level (0 V). Due to this lack of voltage, no current flows through resistor R39 to the base of transistor Q16, causing it to remain deactivated and in the off state, acting exactly like an open switch. As the path to GND is interrupted by Q16, no current can flow through resistor R37. In this scenario, resistor R34 acts independently, pulling the Gate voltage (pin 1) of MOSFET Q13 directly to the full value of +VIN (12 V). As the gate voltage is equal to the source voltage, the gate-source voltage cancels out ($V_{GS} = 0V$), which prevents MOSFET

Q13 from conducting and leaves the OUT1+ terminal and its respective actuator completely without power.

If the aim is to switch on the actuator, the RP2040 sets the G6 pin to a high logic level (3.3 V). With this transition, current begins to flow through R39 and directly activates the base of transistor Q16, forcing it to enter the conducting state (saturation) and operate as a closed switch connected to GND. Once this path to ground is established, current begins to flow from +VIN, passing through resistor R34, continuing through resistor R37, and being drained to GND via Q16. This combined current flow creates an exact voltage divider between R34 and R37, causing the voltage at the gate of Q13 to drop to approximately half the value of +VIN (12 V). As the voltage at the Gate becomes considerably lower than the voltage at the Source, the MOSFET Q13 enters full conduction, allowing the current from +VIN to pass directly to the OUT1+ output and successfully drive the actuator.

In addition, the board incorporates electrical monitoring, analogue acquisition and motor control capabilities via H-bridges, which were not utilised in the implementation.

Sensors

HTU21D - Temperature and Relative Humidity

The accurate monitoring of microclimatic conditions is a fundamental requirement for the automated greenhouse. To achieve this, the HTU21D sensor (Figure 5.8) was utilised to measure both ambient temperature and relative humidity. This specific sensor was selected primarily because it is already incorporated into the Weather Station module of the MOXOH platform. This pre-existing integration streamlined the hardware assembly process and ensured seamless compatibility and communication with the central processing unit.



Figure 5.8: HTU21D digital temperature and relative humidity sensor.³

³<https://www.te.com/>

The HTU21D is a compact digital sensor that communicates with the microcontroller via an Inter-Integrated Circuit (**I²C**) interface. It combines two distinct sensing technologies into a single integrated circuit:

- **Relative Humidity:** The humidity is measured using a capacitive sensing element. This consists of a polymer dielectric layer whose capacitance changes proportionally to the amount of water vapour it absorbs from the surrounding environment.
- **Temperature:** The temperature is measured using a semiconductor band-gap sensor, which relies on the predictable voltage variations across a p-n junction as the temperature fluctuates.

The sensor also features a built-in analogue-to-digital converter (ADC) and a signal processing unit. This allows it to output fully calibrated, high-resolution digital signals directly to the MOXOH platform, minimising the risk of signal degradation or electrical noise interference.

The HTU21D provides a measurement envelope that is exceptionally well-suited for the climatic demands of controlled environment agriculture. Its specifications include:

- **Relative Humidity Range:** It can measure from 0% to 100% RH, with a typical accuracy of $\pm 2\%$ RH within the standard operating range.
- **Temperature Range:** It operates across a wide thermal spectrum from $-40\text{ }^{\circ}\text{C}$ to $+125\text{ }^{\circ}\text{C}$, offering a typical accuracy of $\pm 0,3\text{ }^{\circ}\text{C}$.

These characteristics ensure that the precise environmental parameters required for the successful execution of the grapevine bud forcing process are reliably and continuously monitored.

Raspberry Pi Cam Module 3 - Image Collection

To facilitate the computer vision tasks essential for the automatic identification and counting of inflorescences, the Raspberry Pi Camera Module 3 was integrated into the system. Connected directly to the central processing unit of the MOXOH platform, this camera is responsible for capturing consistent, high-quality visual data of the developing grapevine buds throughout the forcing process. The Raspberry Pi Cam Module 3 is shown in Figure 5.9.



Figure 5.9: Raspberry Pi Cam Module 3 ⁴.

This camera is built around the Sony IMX708 image sensor and interfaces with the MOXOH platform via a standard Camera Serial Interface (CSI). This dedicated, high-speed bus allows for the rapid transfer of high-resolution video and still images directly to the processor, significantly reducing latency and freeing up system resources.

A major technological advancement in this module is its use of Phase Detection Autofocus (PDAF), which replaces the fixed-focus lenses of previous generations. PDAF works by utilising specialised pixels on the sensor to measure the phase difference of light entering from different angles. This enables the camera to calculate the exact distance to the subject and drive a motorised lens assembly to focus rapidly and precisely. For the VineComputer system, this means the camera can autonomously maintain sharp focus on the emerging buds, even if there are slight variations in the distance between the sensor and the plant material.

The hardware specifications of the Raspberry Pi Cam Module 3 make it highly suitable for operation within the dynamic lighting conditions of a controlled agricultural environment. Its key characteristics include:

- **Resolution:** It features a 12-megapixel back-illuminated sensor, which provides the high spatial resolution and fine detail required by the object recognition algorithms to detect small morphological changes in the inflorescences.
- **Autofocus Range:** The motorised autofocus mechanism allows for sharp image capture at very close ranges.
- **High Dynamic Range (HDR):** The sensor natively supports HDR imaging. This capability is particularly critical in a greenhouse setting, as it allows the camera to capture balanced images that preserve detail in both the deeply shaded and brightly illuminated areas of the plant, mitigating the negative impacts of uneven artificial lighting within the chamber.

⁴<https://www.raspberrypi.com/>

Actuators

JOVTOP JT-280T - Water Pump

The primary function of the JOVTOP JT-280T submersible water pump, depicted in Figure 5.10, is to manage fluid circulation within the system, moving water from the reservoir to the tray. Operating on a brushless DC motor principle, it utilises an internal magnetic rotor driven by electromagnetic fields to spin an impeller, which draws water in and expels it via centrifugal force. The operational range of this actuator is defined by a flow rate varying between 280 and 600 litres per hour (L/h) and a maximum delivery head of 60 to 400 cm, depending on the supplied operating voltage, which spans from 6 V to 18 V DC. This specific component was selected due to its high efficiency, low noise emission, and an IP68 ingress protection rating, ensuring reliable and continuous underwater operation.



Figure 5.10: JOVTOP JT-280T submersible brushless DC water pump.

Solenoid Valve

To complement the fluid management and irrigation, a 12 V Normally Closed (NC) solenoid valve, like the one in Figure 5.11, was integrated into the system architecture. The primary function of this valve is to provide precise and automated gating of water flow, preventing unintended leakage and ensuring that fluid delivery occurs strictly when commanded by the central control system.

The operating principle of this component relies on an electromagnetic coil that, when energised with a 12 V electrical signal, generates a magnetic field to overcome internal mechanical resistance and open the fluid pathway.

This valve is designed with no distinction of polarity, which simplifies the physical installation and electrical wiring process. Furthermore, its normally closed configuration serves as an inherent safety mechanism: in the event of a total system power failure, a high-quality stainless steel internal spring automatically forces the valve back into its closed position, completely isolating the water supply.

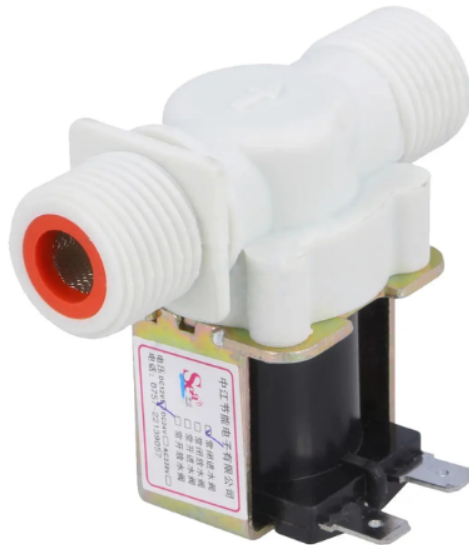


Figure 5.11: 12 V DC normally closed solenoid valve integrated into the VineComputer irrigation circuit.

Sunon KDE1208PTS1 - Ventilation Fans

The Sunon KDE1208PTS1 axial fan is employed to regulate relative humidity within the system's enclosure. It functions on the brushless DC motor principle, where electronic commutation controls a single-coil, 6-pole motor to drive the fan blades, generating an axial air stream. The actuator operates within a fixed performance range at a rated voltage of 12 V DC, producing an airflow of up to 59,5 m³/h at a stable rotational speed of 2850 rotations per minute (RPM). The component was chosen because of its robust sleeve bearing design, low acoustic noise profile, optimal power-to-airflow ratio and the fact that it operates at 12 V DC, a voltage that directly matches the remaining actuators and the chosen power supply. The fan used in this project is shown in Figure 5.12.



Figure 5.12: Sunon KDE1208PTS1 axial brushless DC fan.

ZAWELIYO - PTC Heater

The ZAWELIYO PTC heater serves as the thermal regulation element responsible for increasing the internal ambient temperature. Its operation is based on ceramic Positive Temperature Coefficient (PTC) thermistors, whose electrical resistance exhibits a pronounced increase with temperature. Upon the application of a supply voltage, the PTC element initially presents a relatively low electrical resistance, allowing a comparatively high current to flow and consequently generating heat through the Joule effect. As the temperature of the ceramic material rises and approaches its characteristic transition temperature, its electrical resistance increases sharply. This behaviour inherently reduces the current flowing through the device and, consequently, decreases the rate of heat generation.

The heater therefore exhibits an intrinsic self-regulating mechanism, whereby an equilibrium operating temperature is established when the heat generated by the element balances the heat dissipated to the surrounding environment. This characteristic significantly mitigates the risk of thermal runaway and, in many applications, reduces the requirement for supplementary over-temperature protection circuitry.

This device is operated at 12 V DC, facilitating its integration within the system, and provides a nominal heating power of 180 W, whilst incorporating an integrated fan that drives the generated heat to promote forced convection within the greenhouse, thereby significantly enhancing both heating efficiency and thermal responsiveness. The combination of inherent temperature regulation, operational reliability, compact dimensions, and simplified thermal management makes PTC heaters particularly suitable for controlled heating applications such as the VineComputer. The PTC heater used is shown in Figure 5.13.

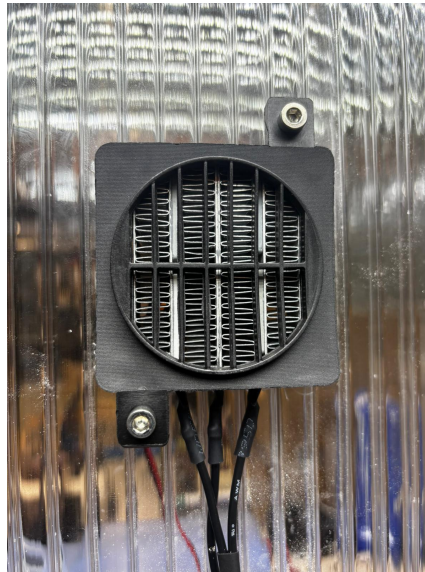


Figure 5.13: ZAWELIYO 180 W PTC ceramic heater.

LED POL ORO33463 - LED Strip

The LED-POL ORO33463 flexible LED strip, such as the one depicted in Figure 5.14, is integrated into the system to provide controlled illumination. It functions via the electroluminescence principle, where Surface-Mounted Device (SMD) semiconductor diodes emit light when a forward current passes through the p-n junction. The actuator features a highly granular actuation range, operating at 12V DC with a nominal power consumption of 14W per metre, yielding a cold white light output of 6,000 Kelvin at a luminous flux of 1,500 lumens per metre (lm/m). The selection was justified by its high luminous efficacy, flexible mounting capabilities, and an IP65 protection rating that shields the circuitry from dust and water splashes.



Figure 5.14: LED-POL ORO33463 flexible LED strip.

5.2 Subsystems

Irrigation System

The irrigation subsystem of VineComputer was designed with two primary objectives: to provide fully automated water delivery with minimal human intervention and to preserve vine health by preventing excessive moisture on the aerial parts of the plants. In viticulture, prolonged wetting of shoots and leaves promotes the development of fungal pathogens and foliar diseases. Consequently, a fundamental design requirement was that irrigation should exclusively target the root zone whilst maintaining the above-ground tissues completely dry. Several irrigation approaches were evaluated during the conceptual design stage. Initially, a direct soil-spraying system was considered, in which each cultivation cell would be individually supplied through dedicated nozzles. Although technically feasible, this solution would require an extensive distribution network composed of pipes and emitters, significantly increasing the mechanical complexity, occupied space, and maintenance requirements of the system.

A second alternative consisted of employing a Cartesian robotic mechanism capable of delivering water individually to each cell. Whilst this approach offered high positional accuracy, it introduced substantial mechanical and control complexity, increased system cost, and reduced overall reliability due to the large number of moving components.

The final irrigation strategy emerged following observations of irrigation practices in greenhouse environments, where capillary irrigation systems are widely employed. These systems supply water at the base of the cultivation trays, allowing the substrate to absorb moisture through capillary action. This mechanism provides efficient hydration of the root zone whilst maintaining the substrate surface and the aerial portions of the plants dry, thereby significantly reducing the risk of fungal diseases.

Conventional greenhouse capillary systems frequently employ gutter-based configurations, in which water flows by gravity along the base of the cultivation trays. However, a critical assessment of this method revealed an important limitation for the intended application. The directional flow of water may lead to non-uniform distribution, whereby the first cells along the flow path receive greater quantities of water and remain exposed for longer periods than those located downstream. Such variability is undesirable in an experimental platform requiring homogeneous growth conditions.

To overcome this limitation, VineComputer adopts a uniform bottom-irrigation approach. Water is introduced simultaneously into a reservoir located beneath the cultivation tray, ensuring that all cells are exposed to identical hydraulic conditions. This configuration promotes homogeneous moisture distribution throughout the substrate and provides consistent irrigation conditions for all plants.

The irrigation system is actuated by a JOVTOP JT-280T water pump, which transfers water from the storage reservoir to the irrigation chamber beneath the tray. In addition, a normally closed solenoid valve is incorporated within the hydraulic circuit to prevent undesired siphoning effects

after pump deactivation. This arrangement ensures that water delivery occurs exclusively during commanded irrigation events and prevents uncontrolled substrate wetting.

Unlike conventional closed-loop irrigation systems, VineComputer does not employ dedicated moisture sensors to determine irrigation requirements. Instead, water delivery is performed using an open-loop control strategy based on the known flow rate characteristics of the pump. The volume of water supplied during each irrigation event is determined by controlling the pump activation time according to $V = Q \cdot t$, where V represents the delivered water volume, Q is the pump flow rate, and t is the pump operating time. By accurately controlling the pump actuation period, the system delivers the precise quantity of water required for complete absorption by the substrate through capillary action, thereby avoiding the formation of excess standing water. This simplified approach eliminates the need for drainage systems, recovery tanks, and water recirculation mechanisms commonly associated with Ebb and Flow systems.

The adopted irrigation strategy therefore combines the advantages of capillary watering with a simplified hydraulic architecture. The resulting system provides uniform substrate hydration, reduced mechanical complexity, improved reliability, and efficient use of both water and available space, whilst satisfying the fundamental objective of fully automated vine cultivation.

Ventilation System

The ventilation subsystem of VineComputer was designed to regulate the internal relative humidity of the greenhouse and thereby maintain environmental conditions favourable to vine development. Excessive humidity levels within enclosed cultivation environments promote the proliferation of fungal pathogens and increase the likelihood of foliar diseases. Consequently, the primary objective of the ventilation system is to maintain the relative humidity near 75% through automatic air renewal.

The controlled variable of the system is the internal relative humidity of the grow chamber. This parameter is continuously monitored by the HTU21D temperature and humidity sensor integrated within the MOXOH Weather Station. The sensor provides real-time measurements of the environmental conditions inside the greenhouse, enabling the implementation of an autonomous humidity control strategy.

The physical implementation of the ventilation system is based on a forced air exchange configuration employing two independent axial fans. One fan operates as an exhaust unit, removing humid air from the interior of the greenhouse, whilst the second fan acts as an intake unit, introducing fresh ambient air from the external environment. This dual-flow arrangement promotes effective air renewal and accelerates the reduction of internal humidity levels.

The ventilation actuators consist of two SUNON KDE1208PTS1 12V DC axial fans. The selection of these devices was motivated by their compatibility with the low-voltage electrical architecture adopted throughout the VineComputer platform. Operating all subsystems from a common 12V DC supply eliminates the need for additional voltage converters or multiple power buses, thereby reducing electrical complexity and improving system reliability.

The control strategy implemented for the ventilation subsystem is based on hysteresis control. This approach prevents rapid switching of the actuators and increases the operational lifetime of the fans. The ventilation system is activated when the measured relative humidity exceeds 80%, at which point both intake and exhaust fans operate simultaneously to promote air exchange. The fans remain active until the relative humidity falls below 70%, at which point the ventilation system is deactivated.

The adopted ventilation strategy provides a simple and robust solution for humidity regulation. By combining continuous environmental monitoring with hysteresis-based control, the system effectively limits excessive humidity, reduces the risk of fungal diseases, and ensures stable operating conditions whilst maintaining low computational and implementation complexity.

Heating System

The heating subsystem of VineComputer was designed to regulate the internal air temperature of the greenhouse and maintain environmental conditions suitable for vine development. Since temperature directly influences plant metabolism, growth rate, and physiological processes, the primary objective of this subsystem is to maintain the internal temperature close to the target value of 25°C, compensating for thermal losses to the external environment.

The controlled variable is the internal air temperature of the greenhouse. This parameter is continuously measured by the HTU21D temperature and humidity sensor integrated within the MOXOH Weather Station, providing real-time temperature measurements for the implementation of the heating control strategy.

The selection of the heating technology was guided by three principal requirements:

1. **Thermal Dynamics:** The system must have low thermal inertia, allowing for rapid heating of the air volume.
2. **Uniformity:** The system must ensure that heat is distributed evenly throughout the growth chamber.
3. **Electrical Compatibility:** The system must be powered by 12V **DC**.

To determine the required thermal power P , the fundamental equation for heat transfer by conduction and convection (5.6) through the greenhouse surface was applied:

$$P = A \times U \times \Delta T \quad (5.6)$$

In which:

- **A (Total Surface Area):** Calculated at 2,1 m^2 , taking into account the geometry of the structure, comprising 4 panels measuring 80 × 50 cm and 2 panels measuring 50 × 50 cm;
- **U (Thermal Transmittance Coefficient):** For the multi-wall polycarbonate used, the value of 3,26 $\frac{W}{m^2K}$ specified by the manufacturer was adopted;

- **ΔT (Temperature Difference):** Defined by the difference between the desired indoor temperature (25°C) and the expected minimum outdoor temperature (10°C), resulting in a temperature difference of 15°C (or 15 K)

Substituting the above values into the formula gives: $P = 2,1 \times 3,26 \times 15 = 102,69\text{W}$. In order to ensure the system's reliability in the event of non-nominal losses or more adverse weather conditions, a safety margin of 20% was applied, resulting in a design power of approximately 123W.

Based on these requirements, the ZAWELIYO PTC heater was selected as the heating actuator, which operates from a 12 V DC supply and provides a nominal heating power of 180 W, exceeding the calculated design requirement and, thus providing additional heating capacity during more demanding environmental conditions. Furthermore, the integrated fan promotes forced convection within the greenhouse, reducing thermal stratification and improving the uniformity of the internal temperature distribution.

The temperature control strategy is also based on hysteresis control. This approach prevents frequent switching of the heating actuator and increases its operational lifetime whilst maintaining the internal temperature close to the desired set-point of 25°C. The heater is activated whenever the measured temperature falls below 24,5°C and remains operational until the temperature exceeds 25,5°C.

Illumination System

The lighting subsystem of VineComputer was conceived not as a means of maximising vegetative growth, but rather as an environmental control mechanism intended to promote consistent and reproducible budburst of dormant vine buds. In grapevine physiology, light acts as an important environmental signal that influences the transition from dormancy to active growth. Consequently, the primary objective of the lighting system is to reproduce the photoperiodic and irradiance conditions associated with spring, thereby providing a controlled and repeatable stimulus for bud development.

Unlike the temperature and ventilation subsystems, the lighting system does not rely on direct environmental feedback or dedicated sensors. Instead, illumination is generated according to pre-defined operating profiles that emulate the gradual variation in solar radiation throughout the day. This open-loop approach was considered appropriate because the objective is not to maintain a measured variable at a specific setpoint, but rather to expose the plants to a controlled and repeatable light regime. The lighting actuator consists of an LED-POL ORO33463 LED strip operating from the common 12 V DC electrical supply adopted throughout the VineComputer platform. The use of a low-voltage LED source provides several advantages, including reduced power consumption, low heat generation, long operational lifetime, and straightforward integration with the existing electronic architecture.

To ensure spatial uniformity of incident radiation, the LED strip was distributed over an area of (80 × 50 cm) using a serpentine arrangement. This layout minimises the formation of shadowed

regions and reduces local variations in radiance. Consequently, all dormant buds are exposed to similar lighting conditions, ensuring that each plant receives an equivalent dose of radiation and improving the repeatability of the experimental conditions. The intensity of the illumination is regulated through Pulse Width Modulation (PWM). This control technique consists of rapidly switching the LED supply on and off at a frequency sufficiently high to prevent perceptible flickering. The average electrical power delivered to the LEDs is determined by the duty cycle, defined as the ratio between the on-time and the total switching period.

The adoption of PWM control offers several advantages compared with conventional analogue dimming methods. Firstly, the LEDs always operate either fully on or fully off, maintaining high electrical efficiency and minimising power dissipation within the driving circuitry. Secondly, the technique provides fine resolution of the emitted light intensity, allowing the irradiance profile to be accurately adjusted throughout the day. Finally, PWM control preserves the spectral characteristics of the LEDs, as the emitted spectrum remains essentially unchanged regardless of the selected duty cycle.

Within VineComputer, PWM control is employed to reproduce the temporal evolution of natural spring sunlight. Rather than applying a constant illumination level, the duty cycle is progressively varied to emulate the gradual increase in irradiance after sunrise and the corresponding decrease at sunset. This approach allows the system to generate artificial day–night cycles that more closely resemble natural environmental conditions, thereby providing a physiologically relevant stimulus for budburst.

5.3 Power Supply

The process of sizing the power supply was based on the identification and analysis of the system's components. These were divided into two main blocks: the actuators and the control module (MOXOH + WS). By consulting the relevant technical datasheets, the voltage V , current I and power P parameters for each component were determined in order to estimate the system's overall power consumption. These parameters are shown in the Table 5.1.

Table 5.1: Actuators parameters

Component	Model	Voltage (V)	Current (A)	Power (W)
PTC Heater	ZAWELIYO PTC Heater	12	15	180
Water Pump	JOVTOP JT-280T	12	0,6	7,2
LED Strip	LED POL ORO33463	12	1,69	20,3
Fans	Sunon KDE1208PTS1	12	0,20	2,6
Solenoid Valve	-	12	0,4	4,8

The MOXOH module incorporates electronic subcomponents that operate at different voltage levels as shown in the Table 5.2.

Table 5.2: MOXOH components parameters

Component	Voltage (V)	Current (A)	Power (W)
Raspberry Pi Cam V3	5	0,6	3
Compute Module 5 (CM5)	5	2,2	11
RP2040	3,3 and 1,1	0,016 (DVDD) and 0.0355 (IOVDD)	0,141
HTU21D	3,3	0,0005	0,00165
AS7341-DGLM	1,8	0,0003	0,0005

The sum of the rated power of these components results in a total power of: $P_{total} = 3W + 11W + 0,141W + 0,00165W + 0,0005W = 14,14W$

Since the MOXOH module is powered by 12 V, the calculation of the input current requires consideration of the energy efficiency (η) of the DC-DC converters responsible for stepping down the voltage. Assuming $\eta = 85\%$, the current consumed by the module at the 12 V input is given by:

$$I_{MOXOH} = \frac{P_{total}}{V_{in} \times \eta} = \frac{14,14W}{12V \times 0,85} \approx 1,40A \quad (5.7)$$

To determine the total system current (I_{total}), the currents of all the components were added to the input current calculated for the MOXOH module:

$$I_{total} = 15,00 + 0,60 + 1,69 + 0,20 + 0,20 + 0,40 + 1,40 \approx 19,49A \quad (5.8)$$

In order to ensure the system's resilience against inrush current, load variations and to allow for future expansion, a safety margin of 25% was applied

$$I_{project} = I_{total} \cdot 1,25 = 19,49 A \cdot 1,25 = 24,36 A \quad (5.9)$$

This process established that the power supply to be selected must provide a voltage of 12 V DC with a minimum continuous current capacity of 24,36 A, thereby ensuring a total power output of at least 300 W under continuous operation.

Based on these guidelines, a market survey was conducted with the aim of identifying commercial solutions that met the stipulated criteria. As a result, the Orno OR-ZL-1639 power supply was selected.

The nominal specifications of this unit exceed the system's minimum requirements, operating at 12 V DC with a current capacity of 33 A and a maximum power output of 400 W. This choice ensures an additional operating margin of approximately 35%, which not only minimises thermal stress and guarantees long-term stability under maximum load conditions, but also provides sufficient capacity to integrate additional components for future prototype improvements.

Chapter 6

Control System and Software

The VineComputer software implementation was designed using a distributed system architecture, utilising the capabilities of the RP2040 microcontrollers present in the various modules and a **CAN** communication bus. The system is functionally divided into three main nodes: the main controller (MOXOH PRO), the Weather Station and the Power Board (AgIoT4Power). To ensure the stability and real-time execution of the greenhouse climate control tasks, an event-driven programming paradigm managed by non-blocking state machines, programmed in C/C++, was adopted.

6.1 Control Logic and State Machines

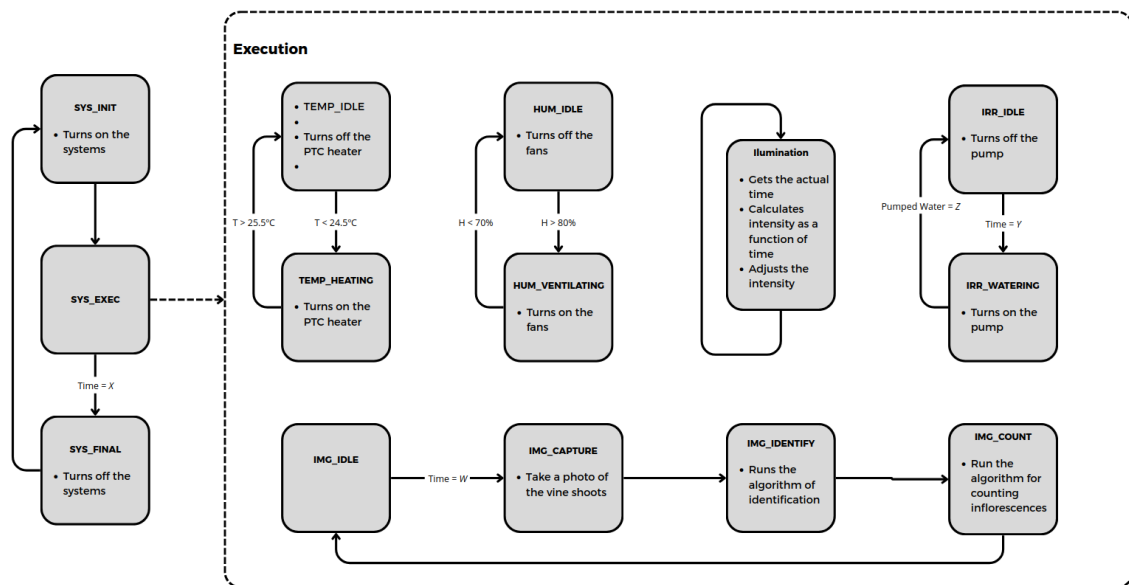


Figure 6.1: VineComputer firmware state machine architecture with five independent sub-machines that run concurrently to control temperature, relative humidity, illumination, irrigation, and image capture.

The control cycle management is divided into a high-level state machine, progressing from system initialisation to the execution phase and, finally, to a termination state. However, it is within the execution phase that the five parallel state sub-machines reside, which control the greenhouse asynchronously, as can be seen in Figure 6.1.

Main State Machine

The top layer of the architecture is implemented via the main state machine, which is responsible for the overall management of the system.

- **Initialisation State (SYS_INIT):** During initialisation, all the operations required to bring the system into a known and safe state are performed. At this stage, all actuators are switched off, the internal timers are initialised, the state submachines are initialised, and the reference times used by the system's timing mechanisms are defined. Once this initial configuration is complete, the system automatically transitions to the execution state.
- **Execution State (SYS_EXEC):** This constitutes the system's main operational state. During this state, the following tasks are performed cyclically:
 1. Periodic requests for new environmental measurements;
 2. Updating of data received from the sensors;
 3. Execution of control state subroutines;
 4. Updating of timing mechanisms;
 5. Processing of events generated by the various modules.

Execution takes place within the programme's main loop, with a cycle of approximately 50 ms. The use of an architecture based on periodic cycles (cooperative polling) avoids the complexity associated with the use of real-time operating systems or multiple concurrent tasks, and is suitable for the scale and timing requirements of the application.

- **Finalisation State (SYS_FINAL):** When the defined trial period is reached, the system transitions to the completion state. At this stage all actuators are switched off and the system enters a standby state until a new trial is started. This mechanism ensures that the experiment ends safely, preventing any actuators from remaining inadvertently active after the trial has finished.

Global Context Structure

All the information required for the system to function is stored in a central structure called `tem_ctx_t`. This structure acts as a shared memory for all modules and contains:

- Internal States - The current states of all state machines are stored;
- Sensor Data - The environmental variables used by the control algorithms are stored;

- Temporal Variables - Several timers are maintained, allowing periodic actions to be performed without blocking the system's operation;
- Processing Variables - Auxiliary control counters.

Centralising this information enables all sub-machines to operate based on a consistent view of the greenhouse's overall status.

Climate Control

The climate control system has been designed according to the principle of functional separation, whereby each environmental variable is regulated by an independent state machine. In this way, changes in temperature do not directly interfere with the logic governing relative humidity, lighting or irrigation.

Temperature Control

The algorithm uses a hysteresis-based strategy to prevent excessive switching of the heater. When the measured temperature falls below the defined minimum limit (24,5 °C), the system activates the **PTC** heater and switches to the heating state (TEMP_HEATING). Heating remains active until the temperature exceeds the upper limit (25,5 °C), at which point the actuator is turned off in the idle state (TEMP_IDLE).

The use of two distinct thresholds creates a dead band that reduces oscillations and increases control stability.

Humidity Control

As with temperature control, two states are used: when the relative humidity exceeds the defined upper limit (80%), the system switches to the HUM_VENTILATING state and the extractor fans are activated. Ventilation remains active until the humidity falls below the established lower limit (70%), at which point it switches to the HUM_IDLE state.

In this case too, a hysteresis strategy is used, reducing mechanical wear on the fans and avoiding excessively frequent switching cycles.

Artificial Lighting Management

The lighting subsystem is designed to simulate the natural light profile throughout the day, so as to expose the vine shoots to photoperiodic conditions representative of spring, the period during which the first inflorescences develop. To this end, a set of PWM-controlled LEDs was used, the intensity of which varies continuously throughout the defined photoperiod. The photoperiod was set to 12 hours, starting at 07:00 and ending at 19:00, times corresponding to sunrise and sunset in Portugal in early spring. The instantaneous intensity ($I(t)$) of the LEDs is not constant during this period, but follows a sinusoidal profile given by:

$$I(t) = \sin\left(\frac{t - t_{on}}{t_{off} - t_{on}} \cdot \pi\right) \times I_{max} \quad (6.1)$$

where t represents the current time in minutes since midnight, t_{on} and t_{off} the limits of the photoperiod, and I_{max} the maximum configurable intensity. This function produces a sinusoidal curve that starts and ends at zero at the extremes of the photoperiod and reaches its maximum value at 13:00, coinciding with solar noon. This profile is depicted in Figure 6.2.

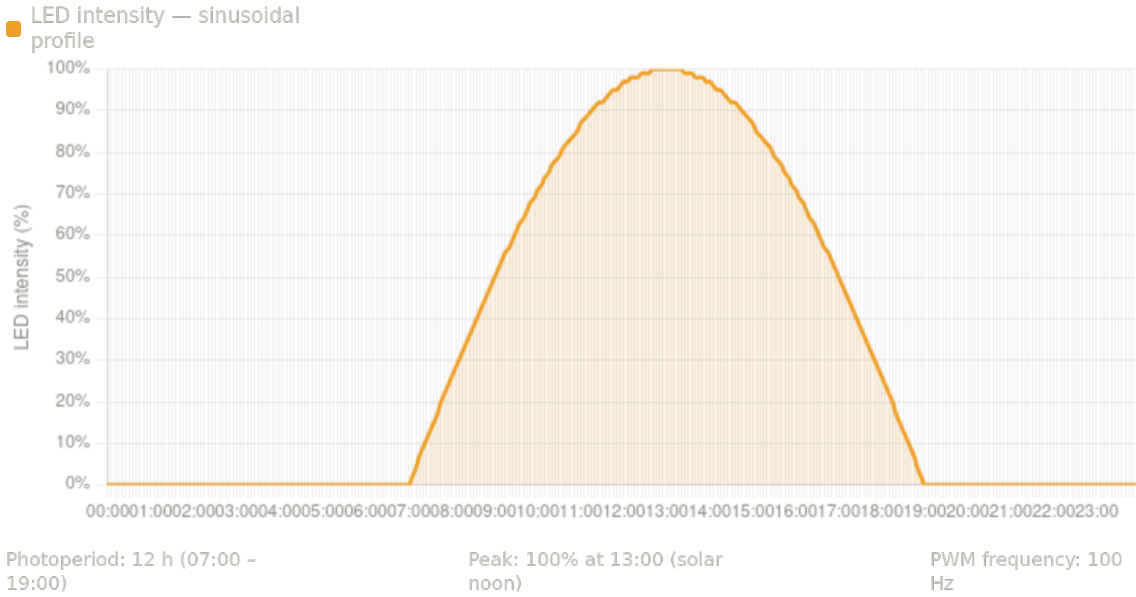


Figure 6.2: Simulated daily LED intensity profile implemented in VineComputer.

The **PWM** implementation was carried out using the RP2040's dedicated peripheral, available via the Pico SDK's PWM library. The **LED** control pin was configured in PWM mode with a wrap value of 9999 and a clock divider of 125, resulting in a frequency of 100 Hz. This frequency was chosen as it lies above the threshold for flicker perception by the human eye, typically between 50 and 80 Hz, thereby preventing visual perception of the LED actuation without imposing unnecessary demands on the hardware. The duty cycle range adopted is from 0 to 10000, corresponding to 0% and 100% intensity respectively, and coincides directly with the internal resolution of the PWM peripheral for the configured wrap value, eliminating the need for any arithmetic conversion.

The system architecture distributes the responsibilities between two nodes on the **CAN** bus. The MOXOH node is responsible for calculating the target duty cycle every minute based on the current time and transmitting it to the AgIoT4Power node via a CAN message using the **CMD_SET_PWM** command. The AgIoT4Power node receives this message and applies the value to the PWM peripheral. The transition to the night-time period is signalled by an explicit **CMD_OFF** command, sent just once at the exact moment the sinusoidal function reaches zero.

To ensure that the lighting profile is referenced to real time rather than system uptime, the controller integrates the RP2040's internal Real-Time Clock (**RTC**) module, initialised at boot via the Pico SDK's RTC library. Since the RP2040 does not feature a backup power supply for the

RTC, the time is entered by the user via the serial port at startup. To prevent the system from locking up in the absence of interaction, a 30-second timeout mechanism has been implemented, after which the system automatically proceeds with a predefined reference time. Once configured, the **RTC** is polled at each lighting update cycle, which has a 60-seconds period in normal operating mode. This corresponds to a maximum duty cycle variation per step of approximately 0.33%, ensuring a perceptibly smooth intensity transition throughout the entire photoperiod.

Irrigation Management

The irrigation subsystem is designed to perform scheduled, automated watering of the cultivation cells without the need for manual intervention. Its control logic is governed by an independent state machine that operates based on time, relying on the internal **RTC**.

The irrigation state machine evaluates the current hour and minute against a predefined daily schedule. The control process is structured around two primary states:

- **Idle State:** The system continuously monitors the **RTC**. When the scheduled time is reached, the controller initiates the watering cycle by transmitting a CAN message with an activation command (CMD_ON) to the AgIoT4Power module, which subsequently powers the water pump (ACT_PUMP) and the solenoid valve. At this moment, the system logs the absolute start time, resets the dispensed volume counter, and transitions to the active watering state. To prevent the system from executing multiple irrigation cycles within the same scheduled minute, a boolean flag (irrigation_done_today) is set to true. This flag is only reset when the internal clock moves past the designated irrigation hour, ensuring a single daily watering event.
- **Watering State:** Because the hardware architecture does not include a direct flow measurement sensor, the controller dynamically estimates the volume of water dispensed. It calculates this volume mathematically by multiplying the elapsed pump operation time by the pump's known nominal flow rate (PUMP_FLOW_RATE_ML_S), calculated empirically as explained in Chapter 9.

The irrigation cycle is terminated, and the state machine reverts to the IRR_IDLE state, when one of two conditions is satisfied:

- The estimated volume of water dispensed equals or exceeds the predefined volumetric target (WATER_DISPENSE_ML).
- The elapsed watering time surpasses a maximum safety threshold. This timeout acts as a crucial fail-safe mechanism, preventing potential flooding or pump damage in the event of calculation anomalies or system faults.

Once either of these stop conditions is met, a deactivation command (CMD_OFF) is issued via the CAN bus to halt the pump.

6.2 Communication Between Modules

Architecture

To ensure reliability, temporal determinism and immunity to electromagnetic interference in the control system, a communication network based on the **CAN** protocol was implemented, in accordance with the **CAN** 2.0A specification. The network topology is a multi-master bus, operating at a stable transmission rate of 500 kbps.

The software infrastructure was developed on the RP2040 family of microcontrollers using the can2040 library. However, the microcontroller's logic lines lack the current capacity and electrical characteristics required to interact directly with the **CAN** bus. To overcome this limitation, the MAX33041EASA+ integrated circuit from Analog Devices/Maxim Integrated was integrated into each node. This is a high-speed **CAN** transceiver adapted for low-voltage systems.

The network consists of three nodes:

1. **MOXOH**: Acts as the system's central coordinator, responsible for executing the rules governing climate control, lighting and irrigation.
2. **Weather Station**: A node dedicated to acquiring environmental data, such as temperature and humidity.
3. **AgIoT4Power**: An actuator node responsible for switching power loads (fans, water pump, **PTC** heater and LEDs).

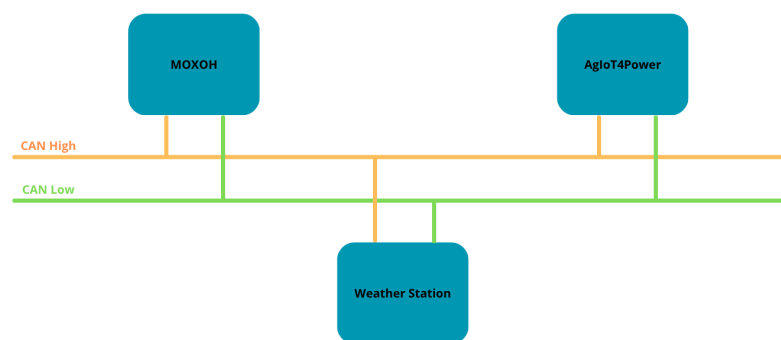


Figure 6.3: Topology of the VineComputer CAN communication network, operating three nodes sharing a common differential bus comprising CAN High and CAN Low lines.

Payload

Although the **CAN** protocol provides robust mechanisms for data transmission, arbitration and error detection at the data link layer, it was necessary to define a custom application layer, tailored to the specific requirements of the system.

In this context, two distinct payload formats were developed: one for controlling the AgIoT4Power's actuators and another dedicated to the acquisition and transmission of data from the Weather Station. Both use standard **CAN** frames with an 8-byte Data Length Code (**DLC**), corresponding to the maximum size supported by the classic **CAN** protocol.

MOXOH → AgIoT4Power

The primary purpose of the communication between the MOXOH module and the AgIoT4Power is to remotely control the various actuators responsible for the system's thermal and hydraulic management. To standardise the control of these devices, a common payload structure has been defined for all command messages, as shown in the Table 6.1.

Table 6.1: Payload structure for communication between MOXOH and AgIoT4Power.

Byte	Field	Description
0	Message Type	CAN message type
1	Command	Command to be executed
2	Actuator ID	Actuator to be operated
3	Reserved	Reserved for future use
4	Value High	Most significant byte of the parameter
5	Value Low	Least significant byte of the parameter
6	Sequence	Message sequence number
7	Reserved	Reserved for future use

The defined structure allows a single frame to carry information relating to the command type, the destination device and an additional parameter associated with the operation.

1. **Message Type:** The Message Type field allows you to distinguish between different categories of messages exchanged between devices on the network.
 - CAN_ID_ERROR = 0x01, Error Message;
 - CAN_ID_COMMAND = 0x02, Command Message;
 - CAN_ID_ACK = 0x03, Acknowledgment Message;
2. **Command:** The Command field specifies the operation to be performed by the selected actuator. Three basic commands are currently implemented:
 - CMD_ON: Turns on the actuator;
 - CMD_OFF: turns off the actuator;

- **CMD_SET_PWM**: Defines a duty cycle for the PWM;
3. **Actuator ID**: This field identifies the physical component that is to perform the requested action.
 - **ACT_PUMP**: Water pump identification;
 - **ACT_PTC**: **PTC** heater identification;
 - **ACT_FAN1**: Fan 1 identification;
 - **ACT_FAN2**: Fan 2 identification;
 - **ACT_LED**: **LED** strip identification;
 4. **Value Field**: Bytes 4 and 5 are used to carry the value associated with the command **CMD_SET_PWM** and represent a percentage multiplied by 100, allowing for a resolution of two decimal places. This value is encoded as a 16-bit unsigned integer that allows values between 0 and 65535 to be represented: $Value = (Byte_4 \times 256) + Byte_5$. For example, to set a duty cycle of 75,00%, the transmitted value will be: $75,00 \times 100 = 7500$ which corresponds to the hexadecimal value 0x1D7E. This approach avoids the need to transmit floating-point numbers, reducing computational complexity and increasing interoperability between devices.
 5. **Sequence**: Byte 6 corresponds to the message sequence number. This field is used to track sent commands, link acknowledgements to the relevant command and detect lost or duplicate messages. Each new transmission increments this value, allowing a direct correspondence to be established between requests and responses.

Once a command has been successfully received and executed, AgIoT4Power sends a confirmation message to MOXOH. The format of the acknowledgement message uses the same general structure as the protocol, containing sufficient information to identify the command that has been executed, as shown in Table 6.2.

Table 6.2: Payload structure for acknowledgement message between MOXOH and AgIoT4Power used in VineComputer.

Byte	Content
0	CAN_ID_ACK
1	Command
2	Actuator ID
3	Reserved
4	Reserved
5	Reserved
6	Sequence
7	Reserved

MOXOH $\longleftrightarrow$ Weather Station

The Weather Station is responsible for collecting environmental variables such as temperature and relative humidity. Unlike communication with AgIoT4Power, the exchange of information follows a request–response model, in which MOXOH explicitly requests a new measurement and the weather station responds by sending a message containing the measurement results.

The process begins with the transmission of a **CAN** message addressed to the Weather Station requesting data collection.

Table 6.3: Data request payload.

Byte	Content
0	SENSOR_READING (0x01)
1-7	0 (0x00)

Receiving this command triggers the data acquisition sequence. Once the acquisition is complete, the Weather Station transmits a **CAN** message, identified by a unique **CAN** identifier (TEMP_HUM_ID). This frame uses all 8 available bytes to encode two 32-bit numerical values: the first 4 bytes correspond to the temperature, whilst the remaining 4 bytes represent the relative humidity.

Table 6.4: Weather Station response payload.

Byte	Content
0-3	Temperature
4-7	Relative Humidity

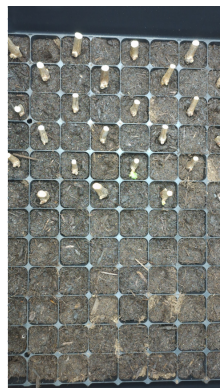
Chapter 7

Perception

The proposed system operates through a computer vision pipeline divided into two sequential phases: image stitching and slot classification. Initially, the system processes two independent images captured by left and right cameras, as shown in Figure 7.1, fusing them into a single panoramic representation of the propagation tray. Subsequently, the pipeline isolates and analyses each individual cell within the tray, classifying its current biological state as empty, cutting, or burst.

7.1 Image Stitching

The foundational challenge in the first phase arises from the physical configuration of the image acquisition setup. Two cameras photograph the same tray with approximately 75% overlap. Fusing these images is complicated by the highly repetitive geometry of the tray grid. The near-identical nature of the cells makes it difficult to ascertain the exact spatial correspondence between the two views.



(a) Image captured by the left camera.



(b) Image captured by the right camera.

Figure 7.1: Raw images captured simultaneously by the two overhead cameras prior to stitching.

To align both images, a Scale-Invariant Feature Transform (**SIFT**) algorithm is employed to detect key points of interest, such as corners and distinct textures, in both images, assigning a unique

mathematical descriptor to each. Following feature extraction, a matching process is conducted alongside a ratio test. The ratio test is crucial in this highly repetitive context, as it eliminates ambiguous matches by discarding points where the best and second-best matching candidates are nearly identical. This effectively prevents the algorithm from erroneously skipping columns within the grid.

With the robust matches isolated, the Random Sample Consensus (**RANSAC**) algorithm is applied to find the largest geometrically consistent subset of points. This process estimates the horizontal displacement between the two images, approximately $dx \approx 642$ pixels, corresponding to the 75% overlap, and rejects any feature correspondences that do not align with this estimated transformation as outliers, resulting in a panoramic image of the full tray such as the one in Figure 7.2.

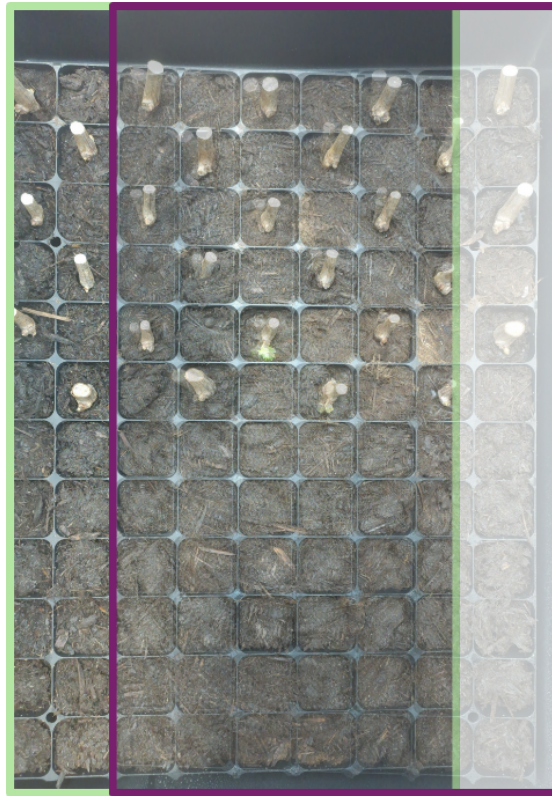


Figure 7.2: Panoramic image of the full propagation tray produced by the stitching pipeline. The purple and grey bounding rectangles indicate the extent of the left and right image contributions, respectively.

Once the images are mathematically aligned, a significant visual challenge remains: the parallax effect (Figure 7.3). A standard feather blending approach, progressively mixing the two images across the overlapping region, is insufficient. While an affine transformation can successfully align a single 2D plane (the soil level), the grapevine shoots protrude several centimetres above this ground plane. Consequently, the tops of the canes appear in slightly different relative positions in the left and right views. A simple blend would result in severe ghosting artefacts, ren-

dering each cane duplicated at half opacity. This phenomenon is unavoidable with a single planar transformation, regardless of the matching accuracy.

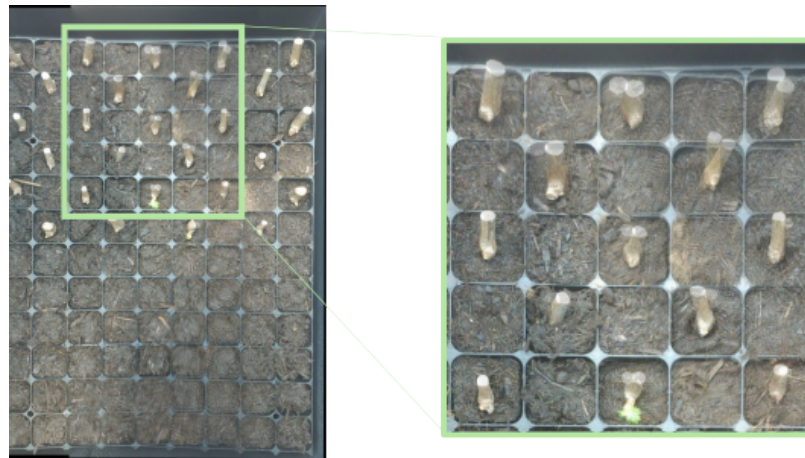


Figure 7.3: Illustration of the parallax effect arising from the dual-camera configuration.

To overcome this problem, a seam-finding algorithm was implemented. Rather than blending the entire overlapping region, dynamic programming is used to trace a precise vertical seam through the overlap based on a computed cost map. The cost function is defined such that areas where the two views show identical ground textures yield a cost near zero, whilst areas where 3D canes appear in different positions incur a high penalty. The resulting seam naturally navigates through the uniform soil and actively routes around the canes.

Consequently, all pixel data to the left of the seam is sourced exclusively from the left camera, and everything to the right is sourced exclusively from the right camera. Each cane appears exactly once, eliminating ghosting (Figure 7.4). To ensure a visually seamless transition, a narrow 30-pixel linear ramp was applied solely along the seam to smooth out any minor brightness discrepancies. Because this transition occurs over uniform soil, the manipulation remains practically invisible.

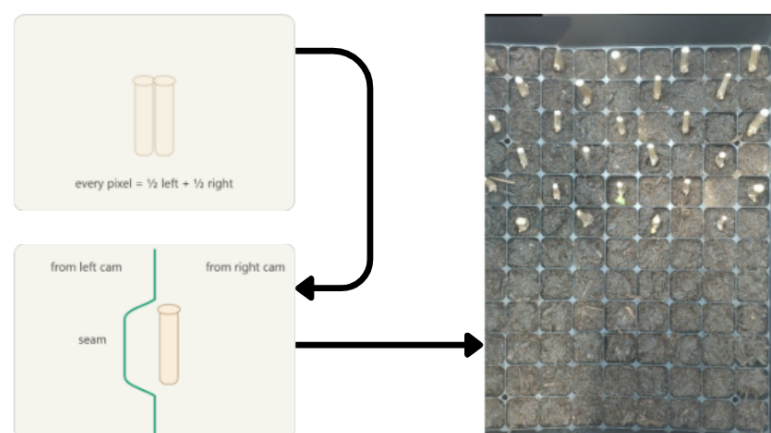


Figure 7.4: Result of the seam-finding algorithm.

7.2 Vision System

The stitching pipeline returns a single top-down image of the tray, but the measurement ultimately wanted is the state of each individual slot. It was tested whether a small image-classification network can label every slot as one of three states:

- **Empty:** No shoot present;
- **Cutting:** A dormant shoot is present;
- **Burst:** A shoot whose bud has sprouted.

The work reported here is a proof of concept. Few canes were available, and the class of interest, burst, was rare, so the resulting dataset is unbalanced and the figures below should be read as an early feasibility test rather than a measure of operational performance.

Image Acquisition

Images of the full tray were acquired over ten separate days, using the two-camera overhead setup described in the previous section. For training the model, the images from the left and right cameras were deliberately processed entirely independently, rather than being merged into a single stitched image. Utilising both perspectives separately proved to be a crucial strategy, as it doubled the number of samples available for training, thereby overcoming the limitations of an initially small dataset. However, this temporary approach does not negate the future importance of image stitching. The unified image will be indispensable for the accurate identification and counting of inflorescences, ensuring that these structures are not double-counted due to camera overlap.

Cell Extraction

Following the generation of the stitched image, the pipeline isolates each individual cell. The algorithm detects the tray's blue-grey plastic dividers by applying a threshold in the RGB colour space, specifically targeting areas where the blue channel is elevated and strictly greater than the red channel. This binary mask is then projected into 1D horizontal and vertical profiles. The peaks within these profiles correspond to the structural positions of the dividers. A regular grid is fitted to these peaks, and mathematical interpolation is used to insert any missing lines that the threshold may have missed. Finally, each detected cell is cropped with a 12% inset to exclude the plastic walls entirely, ensuring only the organic contents remain. These crops are then standardised to a resolution of 224×224 pixels like the ones in Figure 7.5.

Dataset and Labelling

The extracted slots were manually sorted into the three classes. Images from the first nine acquisition days formed the training set, and the tenth day was reserved as the validation set. The tray photographed on the tenth day was prepared with additional sprouted canes, moved in from other

pots, so that the validation set would contain a less marginal number of burst examples. To enlarge the training set, the ninth-day tray was photographed again under two controlled LED illumination levels (0% and 100%), and the training crops were augmented with horizontal mirroring and rotation to limit overfitting.

After sorting, the training set held 12 burst, 307 cutting, and 310 empty slots, and the validation set held 12 burst, 35 cutting, and 121 empty slots. The two sets share the same number of burst slots by coincidence rather than by content: some burst canes appear in both sets, while others do not, because the training set also draws on the ninth-day illumination variants. The imbalance between burst and the other two classes is the main limitation of the dataset and the reason the experiment is presented as a proof of concept.

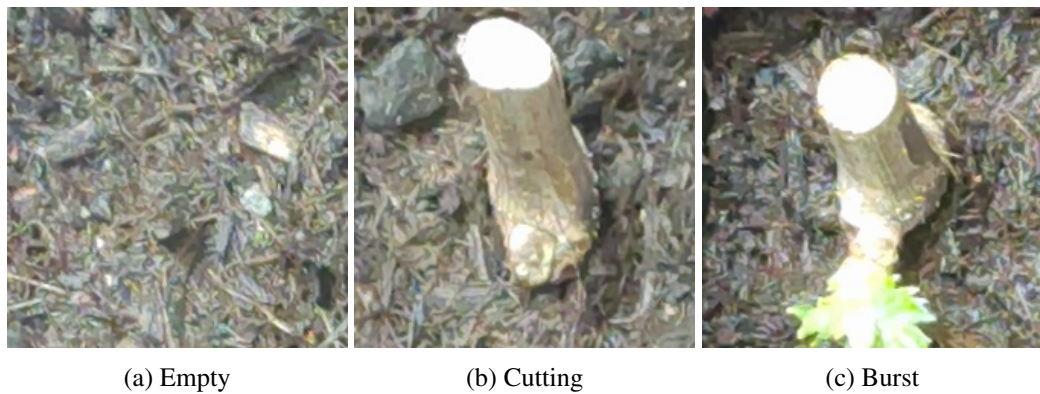


Figure 7.5: Representative 224×224 pixel crops from the propagation tray illustrating the three slot classification classes.

Model and Training

The nano variant of the YOLO26 architecture was used in its image classification mode, since knowing the specific class of an image is sufficient, rather than identifying the location or shape of objects within the image. The nano configuration has the smallest parameter count in the family, which suits a small training set and keeps inference cheap enough for later use on the MOXOH platform. The input resolution was 224 by 224 pixels, matching the crop size from the extraction step. The network was initialised from weights pretrained on ImageNet and fine-tuned on the slot crops. Training ran for 50 epochs, with a batch size of 16 and learning rate of 0,01 on an NVIDIA GeForce RTX 4060 GPU with 8 Gigabytes (GB).

Due to the severe under-representation of the burst class, the model's confidence probabilities for these positive occurrences tend to be relatively low, even when the prediction is fundamentally correct. To counteract this without relying solely on top-1 accuracy, a custom confidence thresholding logic was implemented. The rules are defined as follows:

- A burst prediction is only accepted if the probability $p \geq 0,60$, otherwise, it is reclassified as cutting.
- A cutting prediction is only accepted if $p \geq 0,70$, otherwise, it is reclassified as burst.

- The predictions for the empty class remain unchanged.

This heuristic logic effectively redirects uncertain predictions to their most probable nearest neighbour class, significantly mitigating the risk of false negatives for the rarest and most critical biological state.

Final Outputs

The fully integrated pipeline generates four distinct outputs per execution, providing comprehensive data for further agricultural analysis:

- A CSV file detailing the class, confidence score, grid position (row and column), and bounding box coordinates for each slot;
- A structured directory containing the isolated image crops, organised by grid position and predicted class;
- An annotated visual of the full tray, featuring colour-coded bounding boxes for each class and a header displaying total counts, like the one depicted on Figure 7.6;
- An abstract digital schematic of the grid, using colour-coded squares to represent the spatial distribution of the classes at a glance.

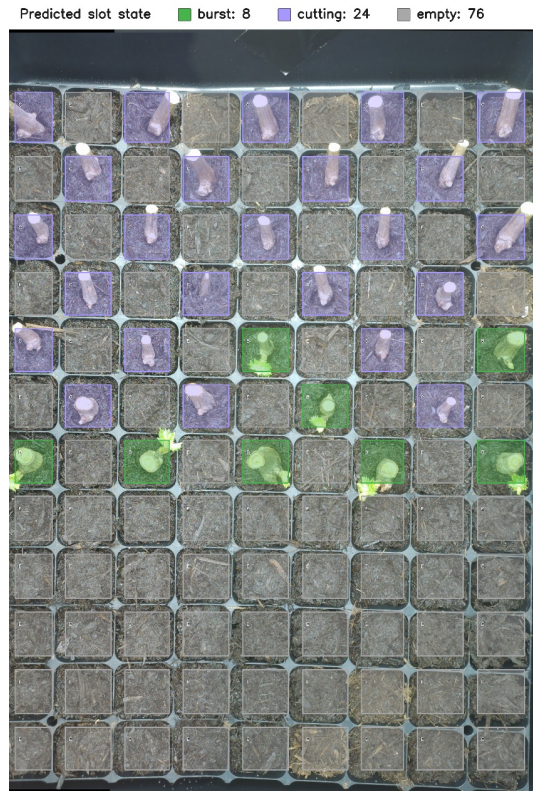


Figure 7.6: Annotated output of the VineComputer perception pipeline applied to the full propagation tray.

7.3 Identification and Quantification of Inflorescences

Due to the experimental timeframe and the natural biological cycle of the cuttings, the grapevines did not reach a phenological stage advanced enough to develop visible inflorescences, preventing the practical validation of the automatic counting phase within this study. Nevertheless, the current perception system serves as a functional proof of concept for the initial stage of a more extensive pipeline, successfully demonstrating automated overhead image acquisition, stitching, the geometric extraction of the grid, and the classification of bud status into empty, cutting, or burst.

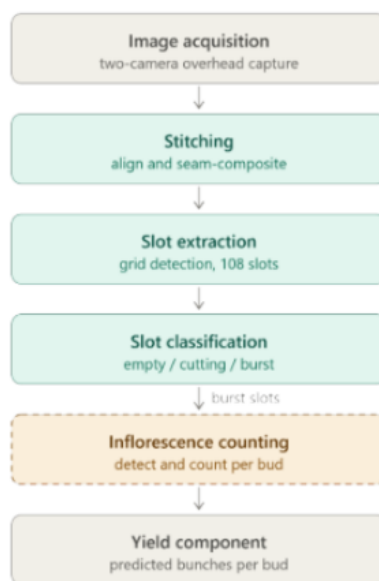


Figure 7.7: Complete VineComputer perception pipeline, comprising the stages validated in this study and the stages proposed for future implementation.

To complete the yield estimation workflow, future work will focus on extending the current modular pipeline by isolating the burst slots and applying a YOLO-based object detection model to identify and count individual inflorescences within each active slot, as illustrated in Figure 7.7. The resulting counts will subsequently be aggregated at tray level, providing both the overall budbreak rate and the mean number of inflorescences per burst bud.

Nevertheless, the successful implementation of this stage depends on addressing several imaging and temporal challenges. Since budburst occurs asynchronously and the developing inflorescences rapidly become occluded by expanding leaves, the trays must be monitored over multiple consecutive acquisition sessions. In addition, the reliable detection of individual inflorescences will likely require higher image resolution or multi-view close-up acquisitions of active slots to reduce the effects of leaf occlusion whilst preserving spatial registration between successive observations.

Finally, the automatically generated counts must be validated against manual assessments and subsequently correlated with field-measured bunch numbers. This validation step is essential to

determine whether the fruitfulness observed under forcing conditions can be used as a reliable predictor of vineyard productivity.

Chapter 8

Implementation and System Integration

This chapter details the construction process of the VineComputer system, covering the physical assembly of the structure, the electrical integration of sensors and actuators, and the alterations made during development. The primary objective is to clearly demonstrate how the hardware components were unified in the final prototype.

8.1 Physical and Structural Assembly

The construction process began with the assembly of the structural base using aluminium profiles. Once the framework was established, the polycarbonate walls intended for the greenhouse were cut. A total of nine sheets were prepared: three measuring 50×80 cm, three measuring 50×50 cm, and three measuring 20×50 cm. These sheets were subsequently mounted and secured to the aluminium structure, ensuring the physical isolation of the cultivation environment.

To allow access to the interior without compromising the seal, acrylic doors were integrated. These were cut to size, resulting in a primary door of 50×80 cm to access the growth chamber and a secondary door of 20×50 cm for the electronics compartment. Next, the necessary holes were drilled into the acrylic for the installation of handles and hinges, culminating in the attachment of both doors to the main structure.

8.2 Subsystems Integration

Irrigation Subsystem

The physical integration of the irrigation subsystem required careful routing of the fluid lines to maintain environmental isolation between the electronics compartment and the growing chamber. To achieve this, a hole matching the exact 10 mm diameter of the supply tubing was drilled through the multi-wall polycarbonate partition panel. This precise fit ensures that the tubing passes between the distinct compartments without compromising the thermal and hygrometric insulation of the climatic chamber.

Subsequently, the tubing was sectioned into two distinct parts: the first section connects the submersible water pump to the inlet of the normally closed solenoid valve, while the second section routes the water from the solenoid valve outlet directly to the tray, as depicted in Figure 8.1. From an electrical and control perspective, both the water pump and the solenoid valve were wired to the same output channel of the AgIoT4Power board (OUT4+). This configuration allows both actuators to be triggered simultaneously by the power interface module, ensuring synchronised water delivery and preventing fluid leakage when the irrigation system is inactive.

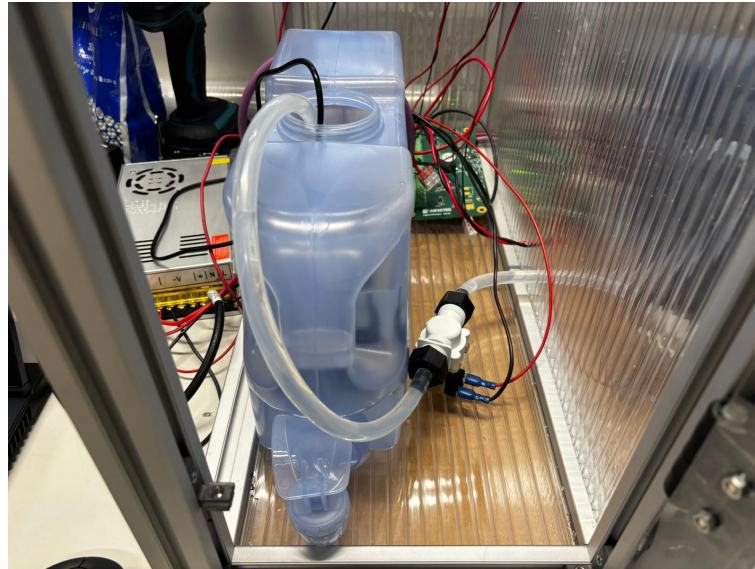


Figure 8.1: Installation of the irrigation subsystem with its supply tubing routed through the partition wall into the growing chamber.

Ventilation Subsystem

For the physical integration of the ventilation subsystem, both extractor fans were positioned near the upper corners of the greenhouse structure, as illustrated in Figure 8.2. This specific placement strategically leverages the natural convection phenomena occurring inside the enclosure. Because warmer and more humid air has a lower density, it naturally tends to accumulate in the upper regions of the climatic chamber. Consequently, the exhaust process is significantly enhanced by combining forced ventilation with the natural thermal stratification of the internal air.

Owing to the elevated location of the fans, it was necessary to extend their electrical wiring to ensure the cables could reach the AgIoT4Power board without being subjected to mechanical strain. To optimise cable management and maintain structural neatness, the extended wires were braided together and secured using dedicated cable mounts along the frame. Finally, the fans were connected to the OUT1+ and OUT2+ output channels of the power interface board.



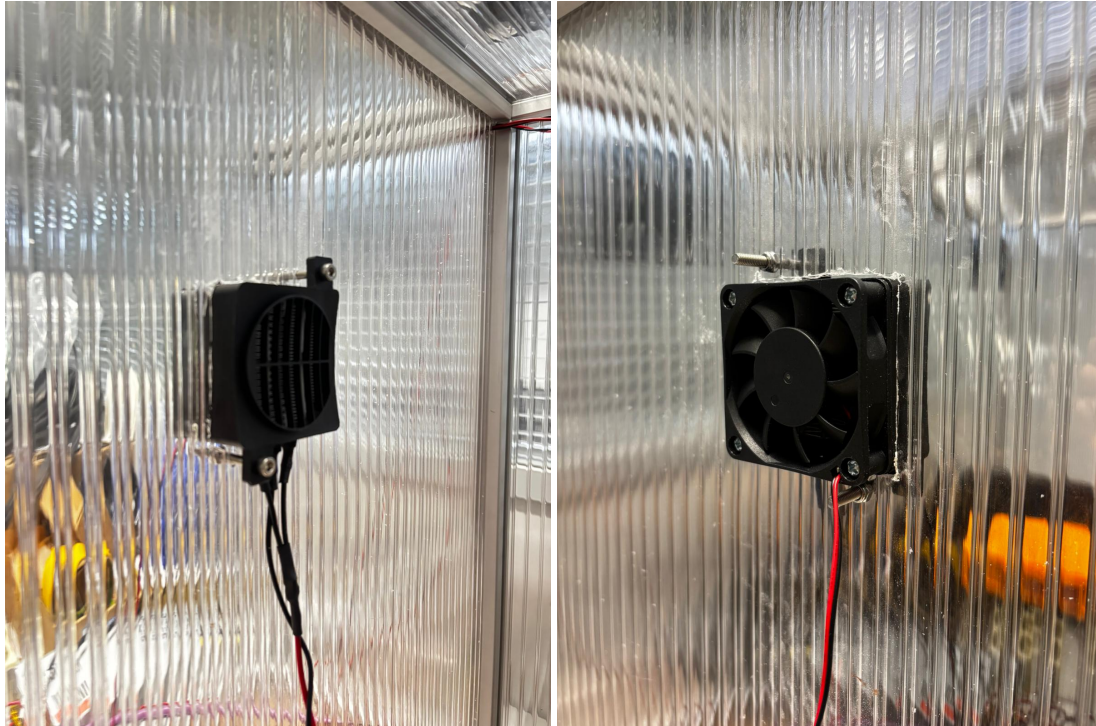
Figure 8.2: Interior view of the VineComputer growing chamber showing the two Sunon KDE1208PTS1 axial fans installed at the upper corners of the rear wall.

Heating Subsystem

The **PTC** heater was installed at the centre of the left side wall of the greenhouse following both practical and thermal considerations. From an electrical perspective, this location minimises the required cable length, thereby reducing wiring complexity, installation effort, and potential voltage losses. From a thermal standpoint, the selected position represents a compromise between the optimal placement for forced convection and the physical constraints imposed by the cultivation tray. Positioning the heater near the bottom of the enclosure would have partially obstructed the airflow due to the presence of the tray, reducing the effectiveness of air circulation. Conversely, placing the heater near the upper section of the greenhouse would oppose the natural tendency of warm air to rise and cooler air to descend, potentially limiting heat distribution throughout the enclosure. The intermediate mounting height therefore promotes efficient forced convection whilst taking advantage of the natural convective circulation within the greenhouse. Furthermore, the heater was installed significantly above the canopy level of the vines, preventing the direct exposure of the plants to the hot air stream generated by the heater.

To install this subsystem, the polycarbonate sheet was cut to the shape and size of the **PTC** heater used and subsequently secured with screws, as shown in Figure 8.3. Following the physical installation of the heater, its electrical cables were extended to ensure they could reach the power

compartment without being subjected to mechanical strain. A dedicated hole was drilled through the polycarbonate partition wall to facilitate the clean routing of these conductors. Finally, the heating unit was securely connected to the OUT3+ output channel of the AgIoT4Power board.



(a) Interior view, showing the heater element

(b) Exterior view, showing the integrated fan.

Figure 8.3: Installation of the ZAWELIYO PTC heater on the centre of the left side wall of the VineComputer growing chamber.

Illumination Subsystem

The integration of the lighting subsystem involved dividing a 5 metre roll of LED strip. This roll was partitioned into ten distinct segments, each measuring 36,5 cm. Electrical wires were carefully soldered to establish the necessary interconnections between the consecutive segments, and each junction was subsequently insulated to ensure electrical safety and system reliability.

To achieve uniform light propagation across the entire surface of the cultivation tray, the segments were mounted in a serpentine layout using double-sided adhesive tape, as depicted in Figure 8.4. The power supply cables originating from the terminal end of this serpentine arrangement were extended to reach the control compartment. These cables were then routed through the polycarbonate partition wall via the pre-drilled cable management holes and securely connected to the OUT5+ output channel of the AgIoT4Power board.

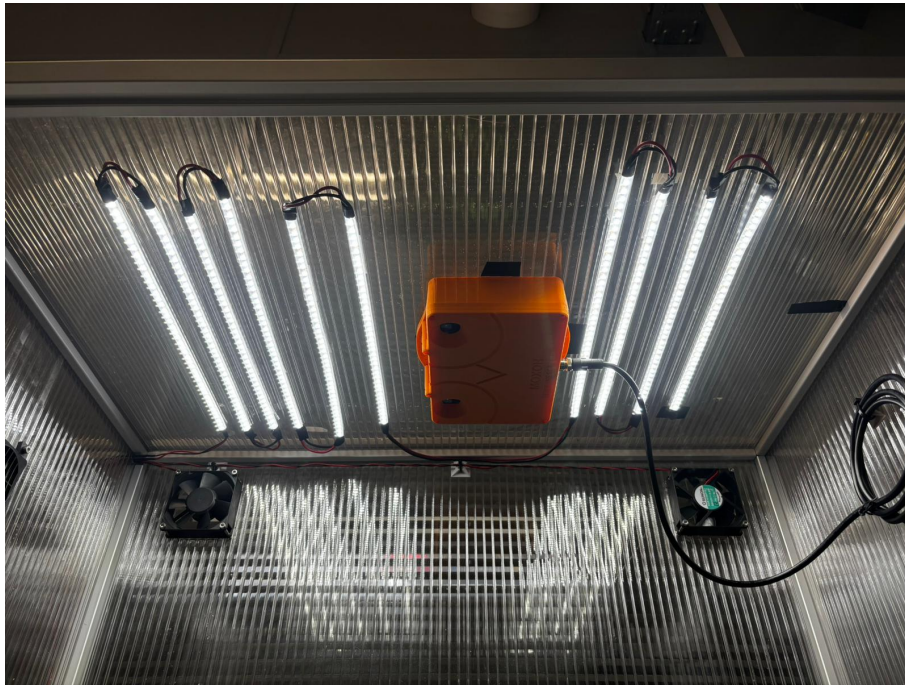


Figure 8.4: Installation of the LED-POL ORO33463 flexible LED strip in a serpentine arrangement on the VineComputer ceiling.

8.2.1 Control Unit and Weather Station

With the physical structure and actuators consolidated, the next phase involved the installation of the perception equipment. Both the MOXOH central unit and the Weather Station were secured inside the structure using high-strength double-sided adhesive tape. This non-invasive approach avoided unnecessary drilling that could compromise the system's thermal insulation and airtightness.

The positioning of the MOXOH PRO central unit was chosen in accordance with the spatial guidelines detailed in Chapter 5. It was strategically mounted to optimise the visual capture of the entire cultivation tray, leveraging its two integrated cameras to ensure comprehensive, stereoscopic, and unobstructed monitoring of the growing area.

Concurrently, the MOXOH Weather Station, and consequently the HTU21D sensor, was installed on the wall opposite the heating unit, positioned specifically in the lower left corner of the enclosure. This location was selected based on several critical thermal and measurement considerations. Spatial and positioning requirements dictated that placing the sensor at the maximum practical distance from the PTC heater minimises the direct influence of the local heat source, ensuring the captured data is representative of the overall greenhouse microclimate rather than the immediate vicinity of the heater. Secondly, the sensor is intentionally located outside the direct path of the forced convection generated by the heater fan, preventing artificially elevated temperature readings caused by the localised hot air stream. Thirdly, the measurement point sits approximately at canopy level, providing environmental readings that closely reflect the actual



Figure 8.5: General overview of the VineComputer physical assembly, showing the consolidated integration of all subsystems.

conditions experienced by the vines. Finally, this location corresponds to one of the thermally less favourable regions of the enclosure, being both below the main convective circulation path and opposite the heating source, where cooler air naturally accumulates. Monitoring this critical area eliminates the risk of local cold zones remaining undetected, allowing the control system to regulate the greenhouse environment based on the most demanding thermal conditions, thereby promoting a highly homogeneous temperature distribution throughout the cultivation chamber.

To provide a comprehensive overview of the integrated system, the global assembly of the VineComputer, showcasing the final consolidation of all physical structures and subsystems, is presented in Figure 8.5.

8.3 Difficulties Encountered and Development Changes

In summary, the physical implementation was primarily characterised by mechanical challenges regarding the manipulation of materials. The main difficulties pertained to the precision required when cutting the polycarbonate sheets to ensure they were straight and accurately measured. Furthermore, strict accuracy was necessary when creating the cut-outs for the actuators (fans and heater), which was essential to maintain the system's insulation without compromising the seal.

The principal alteration made during assembly was the extension of the cabling which, although not initially foreseen, was necessary to ensure proper electrical connections within the final component layout.

Chapter 9

Tests and Validation

This chapter presents the tests carried out on the VineComputer, as well as an analysis of the results obtained. Two tests were carried out: one that examined the behaviour of the greenhouse's climatic variables (temperature and relative humidity) whilst the heater was in operation and another that tested the ability of the VineComputer to maintain the internal temperature.

9.1 Analysis of Thermal and Hygrometric Behaviour Whilst the Heating System is Switched On

The aim of this experiment was to characterise the thermal and hygrometric response of the greenhouse following the activation of the heating system, by assessing changes in temperature and relative humidity over time. The experiment was carried out on the VineComputer at an outside temperature of 22°C. Data were recorded approximately every second by reading the CAN messages sent by the Weather Station, and the data was saved to a Comma-Separated Values (CSV) file.

Temperature

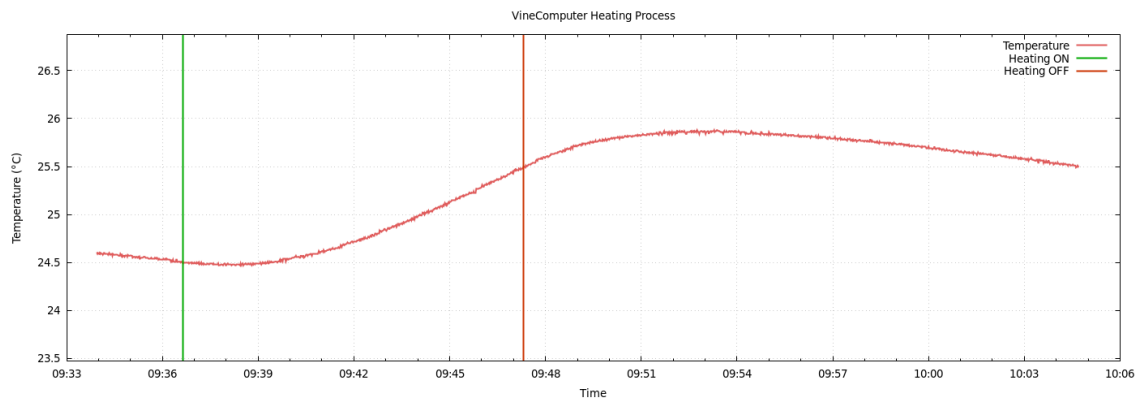


Figure 9.1: Temperature profile recorded during the heating characterisation test.

As shown in Figure 9.1, the temperature initially dropped to 24,5 °C, the predefined threshold on the control unit to activate the heater. Although the PTC was switched on at 09:36:39, the temperature only began to rise approximately 1 minute later. This initial delay is likely due to the system's thermal inertia and the positioning of the temperature sensor, which is located on the opposite side of the heater. After this latency period, the temperature began to rise steadily at an average heating rate of 0,094 °C/min, reaching 25,50 °C at 09:47:19, at which point the heater was turned off.

However, due to the same thermal inertia, the temperature continued to rise for about 5 minutes after the power supply of the heater was cut off, reaching a maximum peak of 25,88 °C at 09:52:45. This behaviour highlights how the greenhouse materials and the heater itself continue to transfer residual energy to the environment even after being deactivated. Following this peak, the temperature decreased slowly, eventually stabilising at around 25,5 °C by the end of the observation period. In total, the temperature difference between the initial minimum and the recorded peak was +1.38 °C and it took about 10 minutes and 40 seconds to reach the target temperature.

Relative Humidity

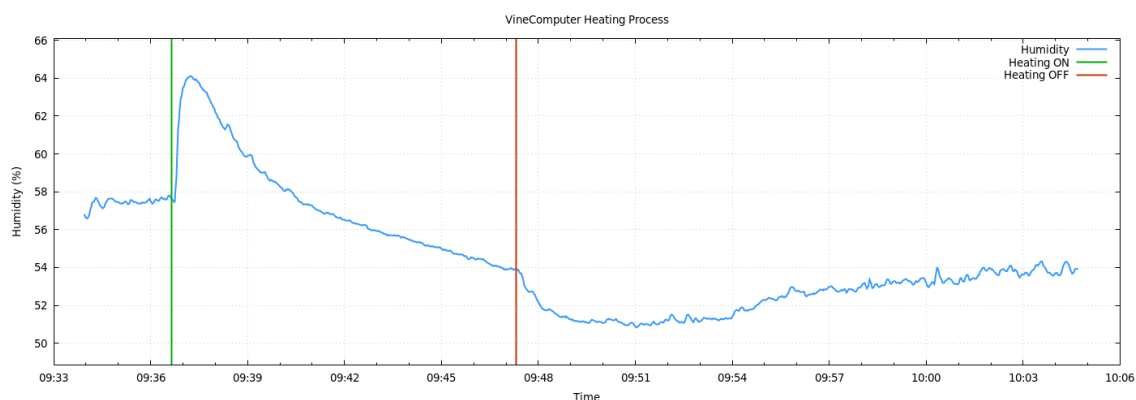


Figure 9.2: Relative humidity profile recorded concurrently during the heating characterisation test.

The humidity behaviour was considerably more dynamic and revealing than that of the temperature. As shown in Figure 9.2, before heating, the readings remained stable between 56,6% and 57,8%. However, just 35 seconds after the PTC was switched on, an abrupt peak of 64.11% was recorded at 09:37:14, representing an increase of approximately +6,7 percentage points compared to the baseline. This initial spike may indicate either a transient convection effect that momentarily altered the sensor reading or a rapid moisture release from the PTC element itself during start-up.

Following this peak, the relative humidity fell steadily throughout the heating period, reaching around 54% by the time the PTC was switched off. This steady decline is explained by the fact that the capacity of air to retain water vapour increases non-linearly, approximately exponentially, with temperature, a principle described by the Clausius–Clapeyron equation. Because there was no physical introduction or removal of water within the greenhouse, the absolute amount of water

in the air remained practically constant. Consequently, as the temperature rose, the maximum capacity of the air to hold moisture increased while the actual moisture content stayed the same, directly driving the drop in relative humidity.

When the heating was finally switched off, an even more abrupt drop occurred, driving the humidity down to a minimum of 50,83%. In the subsequent cooling phases, as the air temperature began to decrease and its moisture capacity contracted, the relative humidity recovered gradually, ultimately stabilising between 53% and 54% until the end of the test.

9.2 Thermal Performance Analysis: Open vs. Closed Door Cooling

To evaluate the thermal dynamics and microclimatic regulation capabilities of the automated greenhouse, a comparative analysis was conducted during the cooling phase. Two distinct operational configurations were tested: one with the greenhouse door fully closed and another with the door open. This investigation aimed to quantify the impact of natural ventilation on the thermal dissipation rate. Throughout both experiments, the ambient external temperature remained stable at approximately 23°C, ensuring a consistent environmental baseline and a uniform initial thermal gradient.

Experimental Protocol and Conditions

Both trials were initiated at a nearly identical internal thermal baseline of approximately 33,0°C. Temperature data was continuously logged by the system's integrated sensors until the internal environment underwent a controlled reduction of approximately 5,0°C, reaching a target threshold of 28,0°C.

- **Door Closed:** The greenhouse was completely isolated from external airflow, relying exclusively on passive thermal conduction through the structural walls to dissipate heat to the cooler 23°C ambient environment.
- **Door Open:** The main door was opened to facilitate natural convective air exchange between the warm internal air and the cooler outside atmosphere.

Comparative Evaluation of Thermal Dynamics

The empirical data collected from the validation trials revealed a distinct variation in the thermal dissipation velocity depending on the ventilation state:

- **Closed-Door Trial:** The internal temperature decreased from 33,0°C to 28,00°C, a net drop of 5,00°C, over a total duration of 75 minutes and 46 seconds, as shown in Figure 9.3. This resulted in a gradual cooling rate of approximately 0,066°C/min.

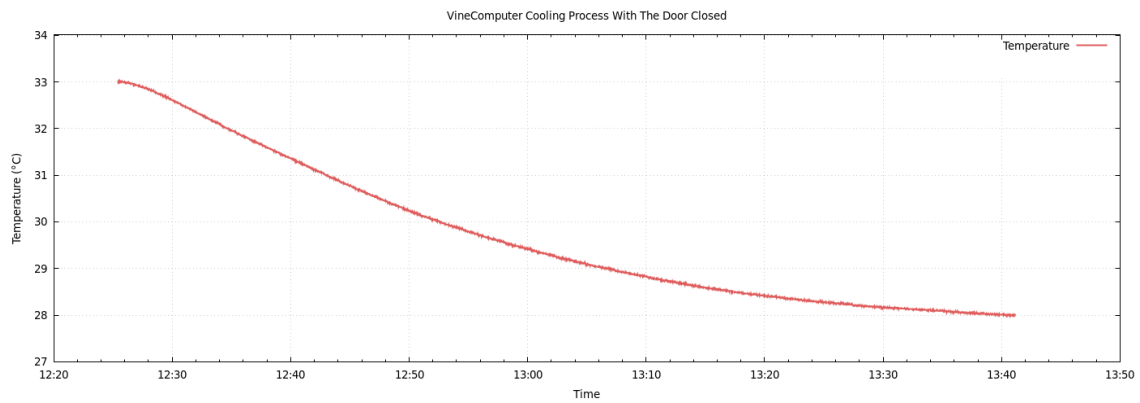


Figure 9.3: Temporal evolution of the temperature inside the VineComputer during the cooling process with the door closed.

- **Open-Door Trial:** The internal temperature dropped from 33,00°C to 28,00°C, which corresponds to a net drop of 5,00°C, in 41 minutes and 21 seconds. This effectively doubled the dissipation velocity, achieving an average cooling rate of 0,122°C/min. This dynamic is depicted in Figure 9.4.

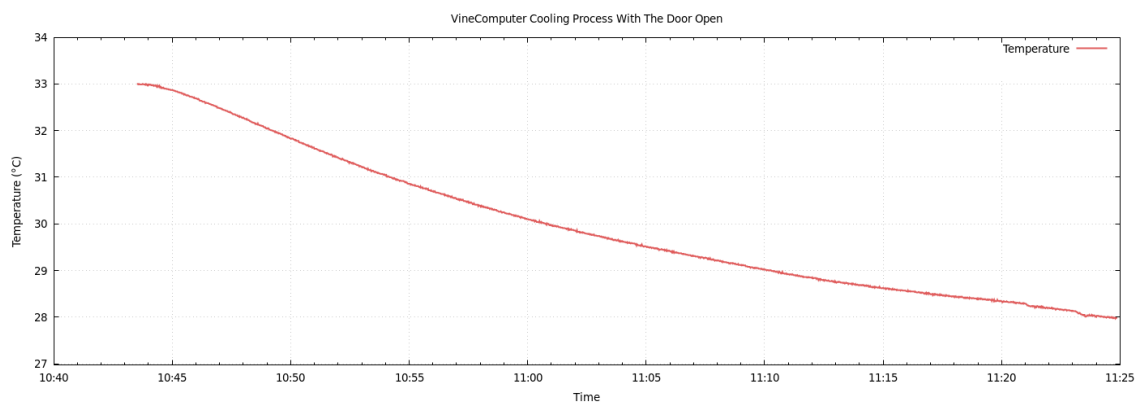


Figure 9.4: Temporal evolution of the temperature inside the VineComputer during the cooling process with the door open.

The activation of natural ventilation via the open door accelerated the cooling process by 45,4%, reducing the required runtime by 34 minutes and 25 seconds to achieve the same thermal reduction. This increase in efficiency was driven by the convective airflow enabled by the initial 10°C differential between the internal greenhouse environment (33°C) and the external ambient air (23°C).

Based on the empirical data gathered, it is demonstrated that the greenhouse successfully fulfils its role in maintaining a stable and controlled microclimate. When completely sealed, the structure exhibits significant thermal inertia and excellent insulation capabilities, losing heat at a very slow and controlled rate (0,066°C/min) despite the cooler external surroundings. This heat retention

capacity is vital for safeguarding budding grapevines against sudden thermal shocks or drastic nocturnal temperature drops, thereby preserving environmental stability.

9.3 Irrigation Calibration

To ensure the precise delivery of water within the VineComputer, a series of calibration tests were conducted. The primary objective was to determine the exact irrigation runtime required to sustain the plants without inducing soil saturation. This was achieved by characterising the water pump's flow rate and determining the substrate's water retention capacity within the specific 12×9 tray layout.

Pump flow rate calibration

The first phase of validation involved measuring the volumetric flow rate of the water pump. To replicate real operating conditions accurately, the entire hydraulic circuit, including the pump and associated piping, was secured in its final operational position. Five separate trials were conducted to measure the time required for the pump to discharge a fixed volume of 600 mL of water. The recorded durations were as follows:

- Trial 1: 9,78 seconds
- Trial 2: 9,60 seconds
- Trial 3: 9,55 seconds
- Trial 4: 9,70 seconds
- Trial 5: 9,73 seconds

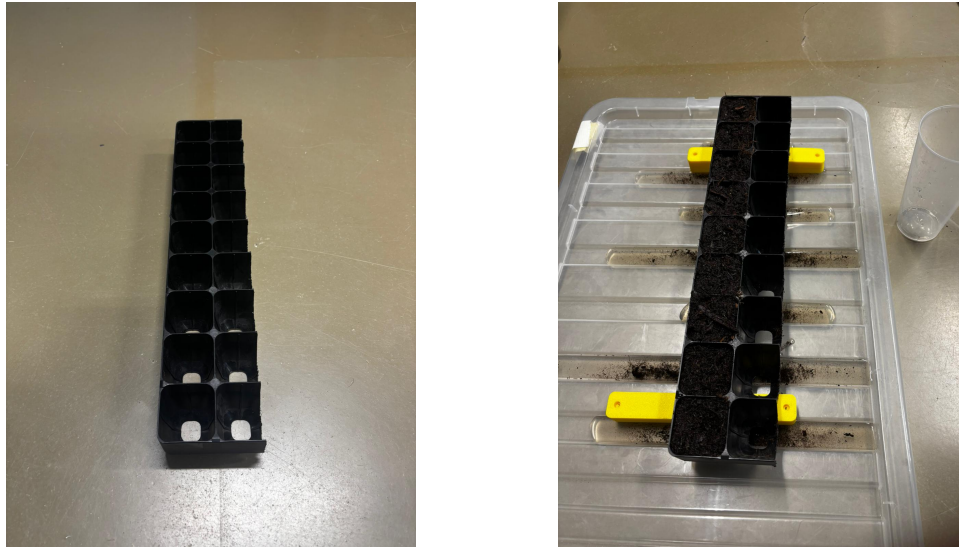
The average time taken to deliver 600 mL was calculated to be 9,672 seconds. Consequently, the mean flow rate of the irrigation system was established at approximately 62,03 mL/s. This empirical value serves as the baseline parameter for the automation software to control the watering intervals.

Substrate saturation and target volume determination

The second phase focused on evaluating the water-holding capacity of the substrate to avoid the physiological risks associated with over-watering, such as root asphyxiation. A representative 18-cell tray section was selected as a sample; however, only 9 of these cells were filled and actively utilised to determine the saturation threshold. The gravimetric analysis proceeded through the following stages:

1. **Empty Weight:** The weight of the 18 empty, dry plastic cells, shown in Figure 9.5a, was recorded at 165 g.

2. **Dry Substrate Weight:** After filling 9 cells with dry substrate, the combined weight increased to 375 g, indicating a net dry substrate weight of 210 g.
3. **Saturated Weight:** Water was progressively applied to the cells until drainage was observed from the baseline openings, confirming complete saturation. Once water ceased to drip, the final weight of the saturated system was measured at 649 g. This process is illustrated in Figure 9.5b.



(a) Empty 18-cell tray section utilised to establish the baseline dry tare weight. (b) Water application to quantify the maximum volumetric retention capacity.

Figure 9.5: Calibration process for determining the substrate water retention capacity using a representative 9-cell sample.

By subtracting the dry weight from the saturated weight (649 g - 375 g), the mass of the retained water was determined to be 274 g. Assuming a standard water density ratio of 1 g to 1 mL, the 9-cell sample retained 274 mL of water at full capacity. To determine the requirements for the entire tray, with 108 cells, this volume was extrapolated by a factor of 12 ($108 \div 9$), which yields a total tray saturation volume of 3288 mL. Because total saturation is detrimental to the development of the grapevine bud, the target irrigation volume was strictly defined at 60% of the maximum capacity. This resulted in an optimal irrigation volume of 1,972.8 mL per irrigation cycle for the entire tray.

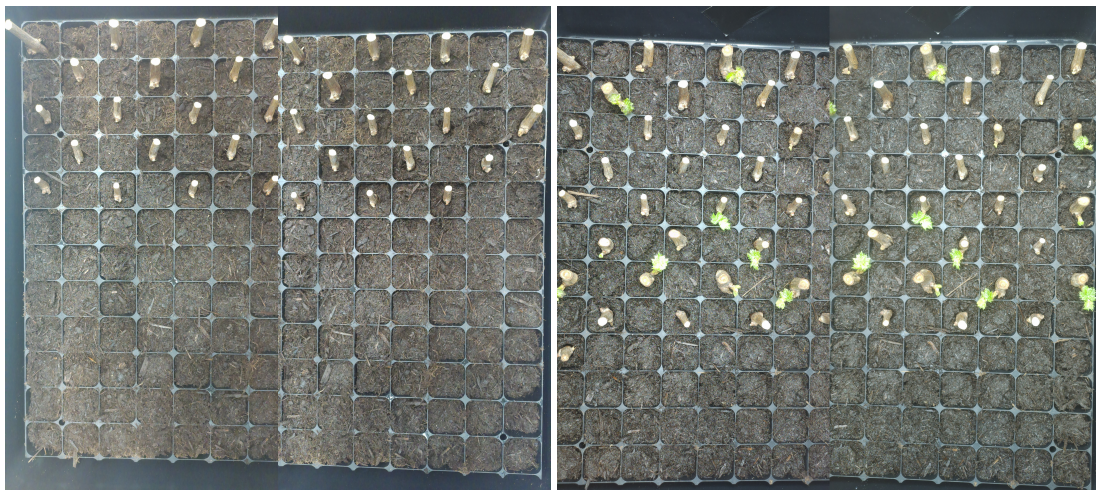
9.4 Bud Burst Induction

Over the course of the ten-day experimental period, the VineComputer autonomously maintained its target climate conditions, a temperature setpoint of 25 °C, a relative humidity target of 75%, and a sinusoidal twelve-hour photoperiod simulating early spring irradiance. Under these conditions, a subset of the dormant vine cuttings placed in the propagation tray successfully underwent

budburst, with visible green vegetative tissue emerging at the bud axis, as can be seen in Figure 9.6.

Although budburst was successfully induced, the cuttings did not reach a sufficiently advanced phenological stage within the experimental timeframe to develop visible inflorescences. The burst shoots remained at an early vegetative stage, exhibiting nascent leaf tissue but not the reproductive structures required for fertility estimation. Extending the experimental duration in future trials is therefore the most direct path to the complete yield-forecasting pipeline.

Notwithstanding this limitation, the successful and autonomous induction of budburst constitutes the core agronomic validation of the prototype, confirming that VineComputer provides a controlled and reproducible environment capable of reliably triggering the biological response upon which the entire productivity forecasting pipeline depends.



(a) Panoramic image of the propagation tray on 1/06/2026 showing the tray at the beginning of the bud forcing experiment. (b) Overhead image of the propagation tray on 25/06/2026, showing the state of the cuttings following twenty-six days of controlled environment.

Figure 9.6: Temporal evolution of the propagation tray during the bud forcing experiment.

It should be noted that, for the purposes of validating the perception pipeline, a number of cuttings that had already reached the burst state in external conditions were transferred into the tray on the final acquisition day, as described in Section 7.2. These correspond to the cuttings visible in the three bottom rows of Figure 9.6b. These introductions were a deliberate experimental decision to ensure a sufficient number of burst examples for classifier evaluation, and do not form part of the evidence for climate-induced budburst. The cuttings that sprouted under autonomous VineComputer control are identifiable from the sequential acquisition record, having transitioned progressively from the cutting to the burst state across successive imaging sessions.

9.5 Perception Pipeline Evaluation

The SIFT-based stitching module was applied to each pair of simultaneously captured frames across all ten acquisition days. In every case, the RANSAC estimator recovered a horizontal displacement of approximately 642 pixels, consistent with the expected 75% camera overlap, and the result was cross-validated by manual inspection of individual cane landmarks. The seam-finding algorithm successfully resolved the parallax artefacts introduced by the three-dimensional structure of the cuttings, producing a fully deduplicated top-down composite in which every slot appears exactly once. The slot extraction routine subsequently isolated all 108 tray cells without systematic misalignment across any session.

The fine-tuned YOLO26 nano classifier was evaluated on the held-out tenth-day validation set of 168 slots, 12 burst, 35 cutting, and 121 empty. Applying the confidence-thresholding heuristic described in Section 7.2, the model correctly labelled every instance, achieving a recall and precision of 1,00 for each class and an overall accuracy of 100%. The confusion matrix is presented in Figure 9.7.

This result must be contextualised carefully: with only twelve burst examples in the validation set, a single misclassification would reduce burst recall to 0,92, so the perfect score carries considerable uncertainty and should not be taken as evidence of generalisation to new cultivars or imaging conditions. It is best understood as a proof of concept demonstrating the feasibility of the approach, with a larger and better-balanced dataset required for a statistically robust evaluation.

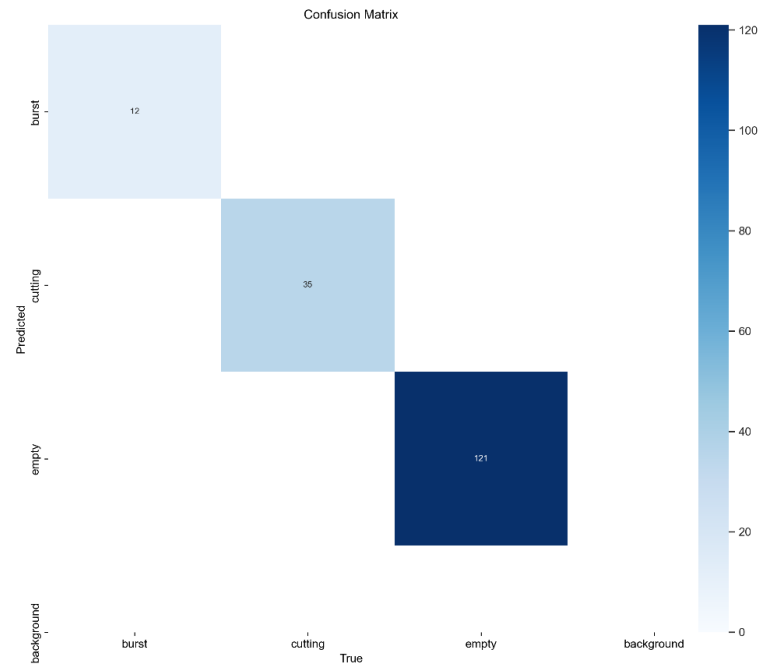


Figure 9.7: 3×3 confusion matrix obtained.

Chapter 10

Conclusions and Future Work

10.1 Conclusions

The work developed in this dissertation represents a significant advance in the field of precision viticulture as no automated system had previously been designed specifically for the purpose of forcing dormant grapevine buds as a means of early yield forecasting. Bud forcing has long been recognised as a reliable and representative technique for estimating viticulture productivity, yet its widespread adoption has been hampered by the considerable labour, time, and technical expertise that its manual execution demands. By embedding this technique within an automated, controlled-environment platform, VineComputer addresses these barriers directly, offering a reproducible and scalable alternative that has the potential to make bud forcing considerably more accessible and attractive to producers and researchers.

The prototype was successfully assembled within the defined dimensional constraints, with the two-compartment design proving effective in protecting sensitive electronics from moisture whilst preserving the integrity of the internal microclimate. The distributed control architecture, based on three nodes communicating over a CAN bus, demonstrated reliable real-time coordination across all subsystems. The climate control system operated successfully throughout the experimental period, with hysteresis-based controllers maintaining temperature and relative humidity within their target bands, and the sinusoidal LED PWM profile faithfully replicating a 12-hour spring photoperiod. Crucially, under these controlled conditions, the dormant vine cuttings successfully sprouted, confirming that VineComputer is capable of inducing and sustaining the bud forcing process.

On the perception side, the image stitching module produced artefact-free panoramic images of the propagation tray, and the fine-tuned YOLO26 nano classifier achieved 100% accuracy on the validation set as a proof of concept. The automatic counting of inflorescences could not be validated within the experimental timeframe, as the cuttings did not reach a sufficiently advanced phenological stage to develop visible inflorescences.

Overall, VineComputer successfully automates the bud forcing environment, induces budburst under controlled conditions, and establishes a solid foundation for a complete yield forecasting

pipeline, representing a meaningful contribution to the digitisation and automation of precision viticulture.

10.2 Future Work

Several directions are identified for the continued development of the VineComputer platform.

The most immediate hardware improvement concerns the thermal efficiency of the growth chamber. Enhancing the thermal sealing at panel joints, door edges, and openings created for certain subsystems would further reduce uncontrolled air infiltration, contribute to greater micro-climate stability between heating cycles, reduce heat dissipation to the external environment, lower the heater's duty cycle, and improve the overall energy efficiency of the system.

A second priority concerns the active regulation of relative humidity during heating cycles. The experimental data confirmed that activating the **PTC** heater produces a consistent and significant drop in relative humidity, driven by the increased moisture-holding capacity of warmer air. In the current implementation, no mechanism exists to compensate for this thermodynamically inevitable effect. The integration of an active humidification system, such as an ultrasonic nebuliser, would enable the control logic to maintain relative humidity closer to the target of 75% throughout heating events, ensuring that the vine cuttings are not subjected to undue desiccation stress, particularly during prolonged or repeated thermal cycles.

The completion of the perception pipeline represents the most scientifically significant area of future development. As detailed in Chapter 7, the current system successfully classifies individual slot states but does not yet detect or count inflorescences within burst slots. Future work should extend the pipeline by training a **YOLO**-based object detection model on images of burst buds at an advanced phenological stage, enabling the automatic identification and enumeration of inflorescences per slot. The resulting tray-level counts would provide the fertility index necessary to extrapolate productivity estimates to the vineyard scale. This stage will also require the collection of a substantially larger and more balanced dataset of burst examples, alongside ground-truth manual counts to enable rigorous model evaluation and correlation against field measurements.

Finally, the development of a dedicated user interface would substantially improve the practical accessibility of the platform. In its current form, system configuration and monitoring require direct access to the firmware and serial terminal, which limits the system's usability outside an engineering context. A dedicated interface, whether a web-based dashboard or a local graphical application, would allow operators to define trial parameters, including photoperiod schedule, temperature setpoints, irrigation volume, and trial duration, without requiring knowledge of the underlying embedded software. An interface like this could also display real-time sensor readings, historical environmental data, and the outputs of the perception pipeline, including annotated tray images and inflorescence counts, thereby providing an end-to-end tool genuinely accessible to viticulture practitioners in the field.

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