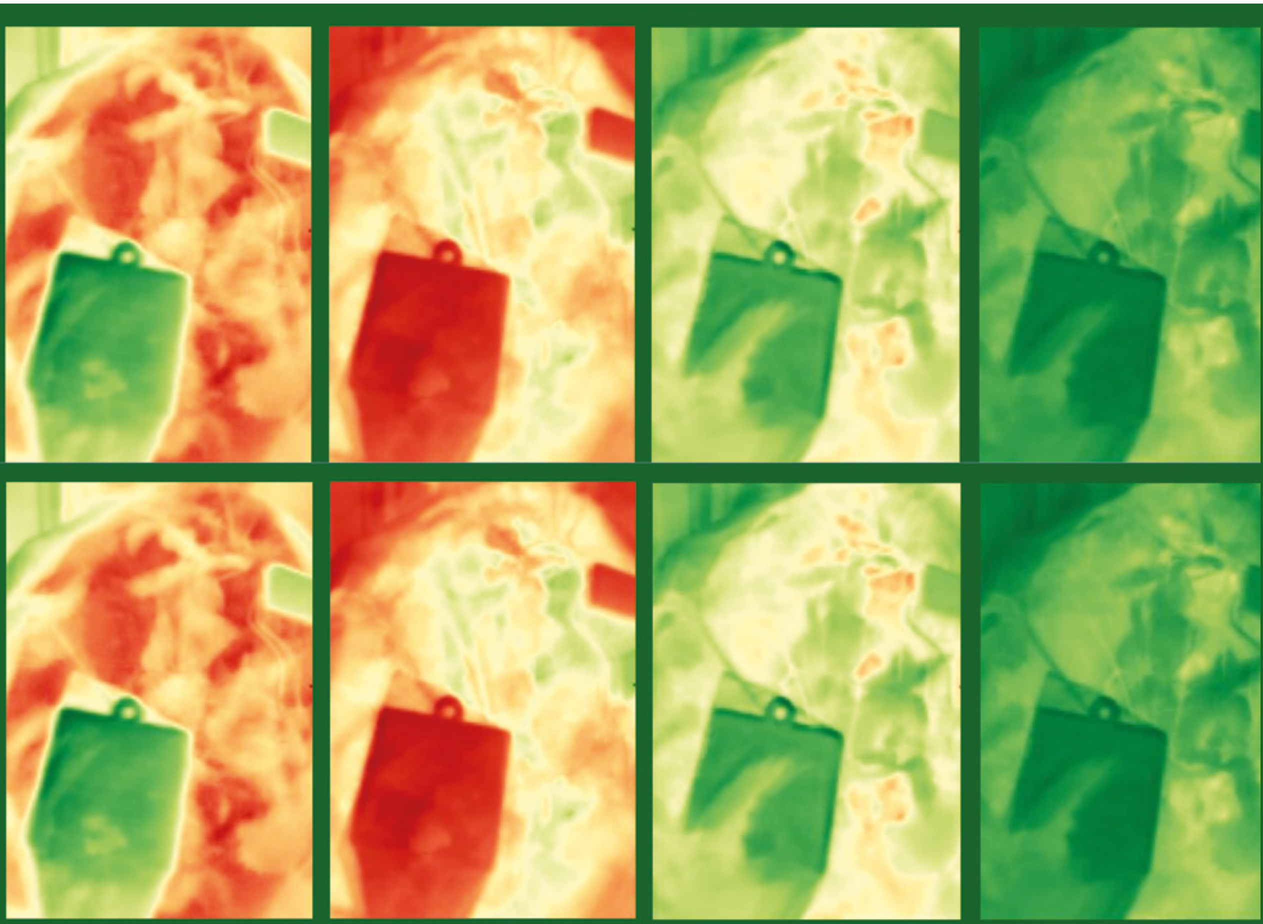
Artūrs Ķempelis

MACHINE LEARNING-BASED MEASUREMENT ESTIMATION APPROACH FOR PRECISION AGRICULTURE

Summary of the Doctoral Thesis



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RIGA TECHNICAL UNIVERSITY

Faculty of Computer Science, Information Technology and Energy

Institute of Information Technology

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DOCTORAL THESIS PROPOSED TO RIGA TECHNICAL UNIVERSITY FOR PROMOTION TO THE SCIENTIFIC DEGREE OF DOCTOR OF SCIENCE

To be granted the scientific degree of Doctor of Science (PhD), the present Doctoral Thesis has been submitted for defence at the open meeting of RTU Promotion Council on July 3, 2026 at 12.00 at the Faculty of Computer Science, Information Technology and Energy of Riga Technical University, Zunda krastmala 10, Room 206.

OFFICIAL REVIEWERS

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DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for review to Riga Technical University for promotion to the scientific degree of Doctor of Science (PhD) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for promotion to a scientific degree.

Artūrs Ķempelis ……………………………. (signature)
Date: ………………………

The Doctoral Thesis has been written in Latvian. It consists of an Introduction, four chapters, Conclusions, 48 figures, 21 tables, and five appendices; the total number of pages is 131, not including appendices. The Bibliography contains 163 titles.

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INTRODUCTION

Since the beginning of the 21st century, smart technologies designed to facilitate agricultural work and improve efficiency and precision have been increasingly used every year. One of the most widely used technologies is IoT networks, which operate sensors capable of measuring the environment of plants and other objects, such as livestock, to improve crop efficiency and enhance food quality (Morella et al., 2023). The use of IoT networks in agriculture provides a significant contribution to productivity and effective production in the cultivation of various plants, including food crops. IoT also includes optical sensor measurements that capture images of plant leaves, which are used after processing in neural network training to enable relatively high accuracy or reliability in recognizing various diseases, such as plant infections (Akilan & Baalamurugan, 2024).

Justification of the relevance of the topic

The task of agriculture is to provide food and resources for humanity. The main task of precision agriculture is to apply technologies to optimize not only the yield volumes obtained but also every aspect of resource usage (which helps maximize yield). Currently, several European Union countries, including Latvia, are trying to implement modern technologies to increase productivity and reduce the negative agricultural impact on the environment. A significant emphasis is placed on the implementation of digital solutions, such as drones with integrated sensors, satellite data, and Internet of Things (IoT) devices (Heyu et al., 2021). Currently, approximately 30–40 % of modern farmers already use at least one type of sensor solution. Furthermore, the amount of public and private investment in such technologies is increasing, including research related to the application of machine learning to improve agricultural efficiency. An increasingly wide range of sensor applications reveals new opportunities to promote sustainable agriculture while reducing costs and enhancing competitiveness in international markets. As a result, sensors have already become an integral part of driving agriculture towards a more efficient and sustainable future (Henrichs et al., 2022).

In addition to various technical challenges, managing sensor data can become overly complex when these sensors operate in large numbers. For example, the volume of data collection, storage, and analysis significantly increases. Considering the recent global situation in agriculture, not all farmers have access to sufficient resources or personnel to process large data volumes, apply machine learning solutions, and ensure sufficient data analysis to enable farmers to make more informed decisions. An increase in data does not necessarily enhance the usefulness of information. Balance can often be achieved with a smaller but strategically placed number of sensors that help address specific issues and optimize resource use. Although sensors help improve processes in agriculture, their unrestricted use is not always the best solution. A relatively better approach would be to select appropriate sensors for specific needs, ensuring that the contribution of technology will be more effective and sustainable (Priva, 2024), (AJ agriplanting).

In agriculture, the implementation of technology enables more precise and informed decisions in cultivation processes. Recently, this has led to an increase in the production of IoT sensor devices, following the demand from farmers. Data is collected on various plant physiological and other factors, which are essential to understand whether cultivation methods are working and whether maximum possible yields will be achieved. Although analyzing these data from sensors already partially allows conclusions about the interrelationships of various data, there is still a lack of research on this relationship (Alireza et al., 2023), exploration on a broader scale and the integration of this information, as well as the capabilities of machine learning models for determining and predicting various sensor measurements. One example and research question in this context concerns the amount of information that could be obtained from different types of sensors, such as plant-safe optical sensor measurements, for example, images obtained in the plant monitoring process in agriculture. How to effectively deploy this information acquisition model in IoT devices and validate it? To help answer the question, the field of study is related to the analysis of environmental measurement data in agriculture during the food crop cultivation process. To improve the performance of existing sensor networks, this Thesis proposes a measurement estimation approach.

The aim and objectives of the dissertation.

The Thesis aims to develop a new approach based on deep machine learning methods that ensures precise measurement estimation in agriculture using a smaller number of sensors compared to existing IoT solutions.

The following tasks were set to achieve the goal:

1. Explore the possibilities of applying deep machine learning algorithms in IoT network systems for plant monitoring.
2. Analyze existing IoT solutions in plant monitoring by evaluating sensor networks, data processing and storage solutions, as well as the integration of machine learning

models in IoT.
3. Develop an environmental sensor measurement estimation model to improve the operation of the plant monitoring IoT network system.
4. Develop a prototype and experimentally evaluate the accuracy and stability of the sensor measurement estimation model.
5. Develop and validate the methodology for implementing precision agriculture measurement estimation.

Theses proposed for defence

The following theses for the development and validation of plant microclimate measurement estimation have been proposed:

1. Using the developed approach for estimating microclimate measurements, which includes a convolutional vision transformer model, it is possible to obtain measurement estimations that are relatively more accurate for relative humidity, light intensity (illuminance), and air temperature sensor measurements than basic convolutional or vision transformer models.
2. By using the trained convolutional vision transformer model for microclimate measurement estimation, it is possible to achieve 80 % or higher accuracy in measurements from sensors of relative humidity, light intensity (illuminance), and air temperature.

The first thesis describes that by applying sensor data processing, analysis, and deep learning methods, experimentally training the convolutional vision transformer and its individual base models (convolutional network and vision transformer), the accuracy of microclimate sensor data estimation will be tested and compared. The second thesis will be confirmed if the sensor measurement estimation achieves precision equivalent to actual sensor measurements.

Object and subject of the study

The object of the Thesis is the IoT network and sensor data intended for microclimate monitoring in food production processes in agriculture. The subject of the research is the methods for processing and analyzing IoT network sensor data, which are suitable for the estimation of plant microclimatic sensor measurements.

Research methods

The Thesis employs literature analysis, comparison, modeling, experimentation, and descriptive methods. Theoretical algorithm analysis is conducted to explore and compare the suitability of different models for the given measurement estimation task. Software development and technology integration methods are used for prototype design.

Scientific novelty and significance of the Thesis

- The Thesis offers a machine learning-based approach that provides measurement estimation by reducing the number of sensors required for these measurements.
- By reducing the number of sensors needed for measurements using a machine learning model, accuracy equivalent to actual sensor measurements is maintained.

Within the framework of the Thesis, a deep learning-based measurement estimation approach was developed, which ensures high accuracy in the estimation of microclimate sensor measurements in agricultural plant monitoring processes.

To demonstrate the functionality and accuracy of the approach, the study involves the development and training of machine learning models by collecting sensor measurements during the plant cultivation process. Within the framework of the Thesis, a method is applied that allows for the automated collection of measurements from multiple microclimate sensors, as well as the automated retrieval and processing of data from thermal radiation cameras. Experiments conducted with the prototype indicate practical applicability in real greenhouse environments for plant cultivation processes.

The developed prototype is experimentally validated using the data collected from microclimate measurement sensors installed on the prototype module, which are compared with the ability of a deep learning-based model to convert thermal radiation image data into accurate sensor measurement estimations. The obtained results, including the accuracy and errors of the estimated measurements, indicate a relatively high estimation accuracy of sensor measurements compared to other methods applied in similar tasks.

After validation, a methodology for implementing the approach was developed, summarizing the insights and conclusions gained during the work process. Results are intended for the implementation of automated sensor measurement estimation models in agriculture for plant monitoring in greenhouses.

Practical significance of the Thesis

Results obtained from real-world environment tests on the effectiveness of the solution can serve as justification for resource investment. For example, if the prototype can significantly reduce costs or time required for a critical process (such as energy consumption optimization or device maintenance), it helps companies clearly justify investments. Consequently, such practical contributions promote long-term competitiveness by reducing unnecessary expenses. Positive implementation results of the prototype can also encourage broader adaptation of the solution in other industries, thereby creating added value and new market opportunities.

Thesis validation

The research conducted in the Thesis and its results were reported and received positive evaluation at 6 international scientific conferences.

1. 2021 IEEE 19th International Conference on Smart Technologies (EUROCON), Lviv, Ukraine, 6–8 July 2021.
2. 9th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE'2021), Riga, Latvia, 25–26 November 2021.
3. The 63rd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS’2022), 6–7 October 2022, Riga, Latvia.
4. 2023 The 10th Jubilee IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), Vilnius, Lithuania, 27–29 April 2023.
5. The 11th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE’2024), Valmiera, Latvia, 31 May – 1 June 2024.
6. 29th International Conference on Circuits, Systems, Communications and Computers (CSCC), Amalfi Coast, Salerno, Italy. 20–24 June 2025.

The main results of the Thesis are reflected in eight publications in international, peer-reviewed scientific journals recognized by the Latvian Science Council.

1. Arturs Kempelis, Andrejs Romanovs, and Antons Patlins, “Design and Implementation of IoT Network Prototype to Facilitate the Food Production Process in Agriculture,” IEEE EUROCON 2021 – 19th International Conference on Smart Technologies, Lviv, Ukraine, 2021, pp. 71–76, doi: 10.1109/EUROCON52738.2021.9535556.
2. Arturs Kempelis, Andrejs Romanovs, and Antons Patlins, “Implementation of Machine

Learning-Based Approach in IoT Network Prototype," 2021 IEEE 9th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), Riga, Latvia, 2021, pp. 1–6, doi: 10.1109/AIEEE54188.2021.9670255.

3. Arturs Kempelis, Andrejs Romanovs, and Antons Patlins, "Using Computer Vision and Machine Learning-Based Methods for Plant Monitoring in Agriculture: A Systematic Literature Review," 2022 63rd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS), Riga, Latvia, 2022, pp. 1–6, doi: 10.1109/ITMS56974.2022.9937119.
4. Arturs Kempelis, Marta Narigina, Eduards Osadcijs, Antons Patlins, and Andrejs Romanovs, "Machine Learning-Based Sensor Data Forecasting for Precision Evaluation of Environmental Sensing," 2023 IEEE 10th Jubilee Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), Vilnius, Lithuania, 2023, pp. 1–6, doi: 10.1109/AIEEE58915.2023.10135031.
5. Marta Narigina, Arturs Kempelis, Andrejs Romanovs, "Machine Learning-Based Forecasting of Sensor Data for Enhanced Environmental Sensing," WSEAS Transactions on Systems, vol. 22, pp. 543–555, 2023, doi: 10.37394/23202.2023.22.55.
6. Arturs Kempelis, Insese Polaka, Andrejs Romanovs, Antons Patlins. (2024). Computer Vision and Machine Learning-Based Predictive Analysis for Urban Agricultural Systems. Future Internet, 16(2), 44. https://doi.org/10.3390/fi16020044.
7. Arturs Kempelis, Andrejs Romanovs and Antons Patlins, "Review on Application of Vision Transformers in IoT Edge Devices for Plant Sensor Measurement Forecasting," 2024 IEEE 11th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), Valmiera, Latvia, 2024, pp. 1–7, doi: 10.1109/AIEEE62837.2024.10586690.
8. Arturs Kempelis, Andrejs Romanovs, Antons Patlins, Rasa Brūzgienė. Machine Learning-Based Measurement Forecasting Approach for Smart Agriculture. WSEAS Transactions on Environment and Development. 2025, 21: 937–949. doi: 10.37394/232015.2025.21.78.

In addition to the Thesis research, the author has been involved in various academic and research activities.

1. The 2023 RTU science and innovation research platform project "Development of a comprehensive model for next-generation IoT networks with enhanced physical layer

security” (project executor).

2. The 2024 RTU science and innovation research platform project “Cybersecure IoT Data-Driven Agricultural Management Research” (project executor).
3. The COST CA22104 project “Behavioral Next Generation in Wireless Networks for Cyber Security” program “Blended Intensive Programme on Internet of Things applied to Environmental Monitoring” (15.09.2023–10.11.2023).
4. Internship at the Universidad Politécnica de Cartagena (Spain), “IoT Applied to Environmental Monitoring” (06.11.2023–10.11.2023).
5. Participation in the “Bosch Artificial Intelligence Spring School” (Bosch Research and Development Centre in Reutlingen, Germany) training on the possibilities and applications of industrial artificial intelligence in chip manufacturing (06.03.2024–07.03.2024).
6. Participation in the international seminar “IEEE Europe & Africa Blockchain Local Groups” (08.09.2021) and presentation of the paper “Blockchain-driven Mobility as a Service”.
7. Member of the local organizing team for the annual international conference “IEEE International Scientific Conference on Information Technology and Management Science of Riga Technical University” (since 2022).
8. Co-author of the article published in RTU ITMS journal: Līva Deksne, Arturs Kempelis, Toms Sniedzins, Armands Kozlovskis (2021). Automated System for Restaurant Services. Information Technology and Management Science, 24, 15–25. doi: 10.7250/itms-2021-0003.
9. Supervision of RTU bachelors' theses and participation in the defence process (2021–2025).
10. Conducting practical and laboratory work in the study courses “Information Technology in Logistics DE0782” and “Information Technology Management DE0650” (since 2021).

Structure of the Thesis

The Thesis consists of an Introduction, four chapters, Conclusions, and a list of references. The introduction defines the aim and objectives of the Thesis, justifies the relevance of the topic, describes the research object and subject, and lists the research methods used as well as the scientific and practical novelty of the work. The introduction concludes with the approval of the study through the author's publications and participation in conferences. The first chapter describes the technologies and sensors used in precision agriculture, their measurements, and the importance of these measurements in the data collection process. The second chapter analyzes the potential of machine learning and computer vision in plant observation, emphasizing the importance of early plant disease and stress predictions for sustainable agriculture. A comparative analysis summarizes how machine learning methods, compared to physical sensors and statistical or other methods, provide higher accuracy, better data fusion, and lower maintenance costs. The third chapter develops and describes a data collection prototype and describes the data collection process. It includes preparation, preprocessing, and initial analysis of collected data. The model architectures are described and selected, and initial model training is performed to determine the most suitable number of training iterations. The fourth chapter develops an approach for measurement estimation. This approach is experimentally tested with sensor measurements obtained during data collection. Model training is conducted, and the results of a total of six developed measurement estimation models are analyzed. A series of experiments is conducted with the developed models using limited training data sets and noise in the input data. Based on the obtained results, an implementation methodology for the approach is developed and described, which can serve as guidelines for implementing the measurement estimation approach in precision agriculture IoT networks. In conclusion, the results achieved in the Thesis and the conclusions obtained through experimental model validation are formulated. The final chapter describes the practical significance of the Thesis, research limitations, and outlines possible future research directions.

1. DATA-DRIVEN GROWING IN PRECISION AGRICULTURE

Precision farming methods aimed at improving plant growing efficiency have gained widespread recognition among farmers globally (Abhishek & Sanmeet, 2023; Alireza et al., 2023). One of the data-driven cultivation approaches in precision agriculture is to address the challenge of growing more without changing the area used for cultivation or by reducing the consumption of resources previously used in agriculture, such as water, nutrients, heat, labor, and other resources. One way to achieve efficient use of these resources is to collect precise measurements from various measuring devices or sensors (Kempelis et al., 2021a). Accurate measurements provide a basis for data analysis and decision-making in various agricultural processes, and such measurements are characterized by taking measurements in places where they would give farmers the most useful information, such as at the roots of plants or on plant leaves, depending on the measurement objective.

Historically, traditional agriculture has relied on uniform management practices, ignoring changing field conditions, often leading to resource wastage, such as inefficient use of plant-specific chemicals or nutrients, including various soil enrichers (Padhiary et al., 2025). The introduction of precision or smart agriculture significantly reduces this inefficiency through real-time data acquisition using various types of sensors and Internet of Things devices (Waleed, 2021).

In the last 8 years, the implementation of sensors in agriculture has shown consistent growth. Specifically, the market share of agricultural sensors has increased from USD 1.05 billion worldwide in 2017 to USD 2 billion in 2023, and is forecasted to exceed approximately USD 2 billion by 2027 (Fig. 1.1), continuing to rise (Kbvresearch, 2022).

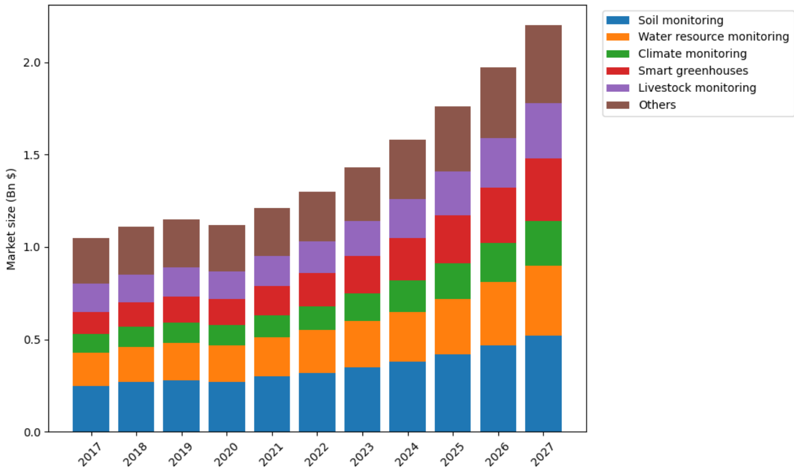

Fig 1.1. Agricultural sensor technology market shares, by application, years 2017–2027 (sourced from (Kbvresearch, 2022)).

Certain market forecasts also provide information for the year 2030, where the expected market share of sensors used in agriculture could reach USD 4.6 billion (Grandviewresearch, 2023). However, these trends create significant pressure in the field of sensor maintenance. As the number of devices increases, operating and maintenance costs also rise sharply, and it may not be cost-effective for farms to use them in the long term. A large number of devices come with a proportionally high risk of device failure, requiring manual employee intervention. The devices themselves are subject to various environmental factors, such as ultraviolet radiation, agrochemicals, floods, damage caused by livestock, or other types of damage. Sensors that measure moisture, nutrient content, and similar metrics gradually lose their accuracy and may require periodic calibration, which can involve dismantling the device, calibrating it, possibly servicing it, and reinstalling it.

The result also shows relatively new trends related to the exploration of collected sensor measurement data, sensor calibration, their fusion, and self-calibration methods. Various data analysis, data mining, and machine learning-based methods (Padhiary et al., 2024) allow the discovery of correlations in measurement data and potentially enable measurements to be made with a reduced number of physical devices, thus creating savings in measurement device resources without changing the overall significance or efficiency of the sensor network. Sensor data collected during the plant growing process can be used for analysis and decision-making or information retrieval (Kempelis et al., 2021b), which helps farmers or automated control equipment make decisions to provide plants, for example, with various nutrients.

2. RESEARCH OF MACHINE LEARNING METHODS FOR IMAGE ANALYSIS

Machine learning technologies have created significant potential in agriculture, especially in the field of plant growth monitoring (Habib et al., 2022). The useful application of machine learning technologies provides widely applicable tools for plant monitoring, such as early detection and forecasting of various plant health issues, which are important for sustainable and efficient agriculture. Various algorithms are capable of analyzing large data sets obtained from microclimate sensor measurements and images captured by various optical devices used in agriculture. Regression models or decision trees based on computer vision can detect hidden patterns and relationships in measurement data. In the context of plant observation, this means that algorithms can predict plant health status by analyzing historical data and current observations. Such an approach for early health status prediction means timely risk identification, allowing for preventive measures to prevent possible health problems or the spread of various diseases (Badidi, 2023).

The study by Almutawa and Eid (2023) describes the inclusion of infrared radiation or thermography in soil moisture detection processes, offering a non-invasive and contactless method that can significantly enhance existing plant monitoring systems. Using a halogen lamp and an infrared camera to capture soil surface temperature, the study demonstrated a close correlation between thermal readings and soil moisture levels. Successful moisture content determination in this way shows the potential of thermal radiation detection, serving as a valuable tool in precision agriculture, allowing careful monitoring of soil conditions without direct physical impact on the soil or the plant itself. The studies also found a pronounced inverse relationship between soil surface temperature and moisture content – as moisture decreased, temperature increased, and vice versa. This discovery is significant in plant monitoring as it proves that thermal data can reveal crucial environmental factors, such as soil moisture, which directly affect plant health. The ability to obtain such measurements from thermal images opens opportunities to develop complex machine learning models to predict various measurements related to plant monitoring. Combined with the analysis of the transpiration process, it would be possible to develop more accurate plant microclimate observation models.

Considering that the application of computer vision creates a new dimension of information, allowing the analysis of plant visual cues to predict plant well-being, physiological properties, health, and growth processes, it theoretically could enable the development of an approach for evaluating various sensor measurements based on microclimate or plant visual features. Computer vision, for example, using convolutional neural networks, plays a significant role in precision agriculture processes (Liu et al., 2023). Convolutional networks are widely recognized in computer vision context tasks and are frequently applied as a deep learning method that demonstrates high efficiency in processing and interpreting large volumes of visual information data obtained from plants during their growth process. Convolutional networks are applicable in tasks such as detecting disease symptoms, nutrient deficiencies, or pest infestations by analyzing images of plant leaves and fruits (Kempelis et al., 2022). Recently, vision transformers (ViT) have been increasingly applied in computer vision tasks, which, like convolutional networks, are part of the deep learning approach and originated from the transformer architecture used in large language models for natural language processing (Dosovitskiy et al., 2020). Vision transformers are often recognized in literature for claiming to demonstrate relatively higher accuracy in experimental studies compared to, for example, convolutional neural network models. Although each of these models has its advantages and disadvantages, the latest studies frequently compare these models, and some studies also propose combining these model architectures (a hybrid model approach that combines the advantages of both CNN and ViT models) to improve accuracy in various applications, such as object recognition (De Silva & Brown, 2023). Currently, vision transformers are not yet widely used for estimating or forecasting plant environmental factors (such as air temperature or other significant plant growing process measurements) – this approach is not sufficiently researched or published in scientific databases. Based on the findings from literature analysis, it can be concluded that the microclimate encountered in plant cultivation is nonlinear and variable – sensor measurements depend on the impact of the microclimate, soil type, and plant phenology, the data flow is continuous and often can be incomplete (with missing information or data). Machine learning algorithms are designed for structuring such large-scale, multidimensional data, revealing hidden relationships that statistical methods often fail to capture. Machine learning methods are intended for various types of input data, such as combining plant leaf thermal image frames with soil moisture sensors or other measurements or predictions, thereby providing meaningful (measuring where most needed) and accurate (with minimal error) calculations.

Regression models based on a convolutional network architecture are reliably capable of expressing continuous values from visual data, ranging from determining soil moisture levels using information from various types of images to predicting yields from satellite images. This demonstrates that the application of machine learning methods could potentially replace relatively expensive measuring devices by converting various types of visual information into quantitative measurements.

Physical sensors, while maintaining accuracy, provide limited information about the location where they are installed, whereas statistical methods like interpolation maps become inaccurate if lighting, soil background, or other properties change. Deep neural network models can learn nonlinear relationships between images and actual microclimate measurements without manually created heuristics. The implementation or expansion of physical sensor networks can quickly become disproportionately expensive, as each additional sensor requires hardware, installation, and calibration or maintenance. Machine learning-based virtual sensors or measurement predictions can integrate physical measurements with various types of images, creating microclimate measurement maps using only a fraction of the required hardware. In conducting individual measurements, traditional methods rarely utilize diverse data types or information sources.

Sensors require periodic calibration and are susceptible to environmental conditions, including their impact, especially in agricultural applications. Once machine learning models are trained, optimized versions by size can operate on devices with limited resources. Variants like *MobileNet*, *MobileViT*, and similar provide sufficiently fast inference while maintaining high accuracy. The implementation of statistical methods is relatively simpler, but they lack the prediction accuracy needed in various changing scenarios characteristic of the agricultural environment.

Classical calculation methods or heuristics can be sensitive to light angle, soil background, and rapid changes in weather or microclimate. Machine learning models, through measurement estimation, reduce the number of missing data records in cases where individual sensors stop working or incoming data streams become irregular. Machine learning models can output practically usable indicators (yield volume, disease risk, required irrigation or other resource amounts) that are directly usable by farmers in the decision-making process.

In all previously reviewed criteria, including accuracy, scalability, costs, data integration, model adaptability, and deployment, machine learning methods achieve equivalent and often pronounced superiority compared to direct measurement capabilities, as well as statistical, interpolation, or heuristic methods. Therefore, in the context of modern precision agriculture, where conditions are frequently changing, budgets are limited, and decisions must be made promptly, machine learning is comparatively the most suitable and cost-effective method for estimating measurements within the plant growing process.

3. DEVELOPMENT AND TRAINING OF MACHINE LEARNING MODELS

To explore the identified gaps from studies found during literature analysis on sensor measurement prediction and estimation in agricultural environments, this study involves the development of a measurement estimation approach. The study proposes a new approach capable of operating in precision agriculture environments where various plants are grown and monitored. The proposed sensor measurement estimation approach includes capturing and processing images from a thermal camera, then using these thermal images as input to a machine learning model for estimating sensor measurements, such as illuminance (hereafter referred to as light intensity), soil water content, and relative humidity. To develop this approach, it is necessary to obtain sensor measurements for use in data analysis and measurement prediction or estimation. Considering that the datasets and studies revealed during the literature analysis do not include open datasets with thermal radiation images and temporally and spatially coincident sensor measurements, the decision was made to create this dataset within the scope of the Thesis. Based on the obtained measurements, the most suitable methods for data analysis were selected, and the approach to perform measurement estimation from thermal image input data was experimentally validated.

3.1 Data collection process

The Thesis aims to perform measurement estimations in the same environment and time where thermal images are captured, hence it is necessary to prepare a prototype sensor measurement collection module in a real agricultural environment. This is done to determine the most suitable method and models for measurement estimation. Various types of sensors and devices were used in the creation of the data collection prototype module to obtain information that is critically important for plant health. Various sensors were used in the development of the prototype module, whose main task is to ensure automation of data collection.

- FLIR Lepton 3.5 radiometric thermal camera with a 57° lens (GroupGets, 2024), chosen because it provides radiometric measurements, where each image pixel is given a calibrated temperature value, rather than just a relative heat image.
- FLIR Lepton camera interface and additional connection module PureThermal2 (GroupGets PureThermal 2, 2024), used to ensure data exchange between the thermal camera and the single-board computer.
- VEML7700 – for determining light intensity levels (Elektrokit VEML7700, 2024),

chosen because it provides an I2C interface, high measurement accuracy, low sensor power consumption and a relatively wide measurement range.

- HDC1080 – for measuring relative air humidity and air temperature (Rosen et al., 2020), chosen because it provides an I2C interface, has a wide measurement range and relatively high measurement accuracy and low power consumption.
- Single-board computer Khadas, model VIM 1S (Khadas, 2022), chosen because of its low power consumption and suitability for automated measurement systems. The device is based on a quad-core ARM Cortex-A35 processor (up to 2.0 GHz), with built-in 16 GB eMMC memory and provides sufficient computing power for real-time data processing.

Sensors used for environmental measurements are connected to the single-board computer Khadas (Fig. 3.1) using separate plug-in connections (GPIO, visible on the right side of Fig. 3.1). To ensure a circuit with a minimal number of connections, the sensors are linked in two I2C buses.

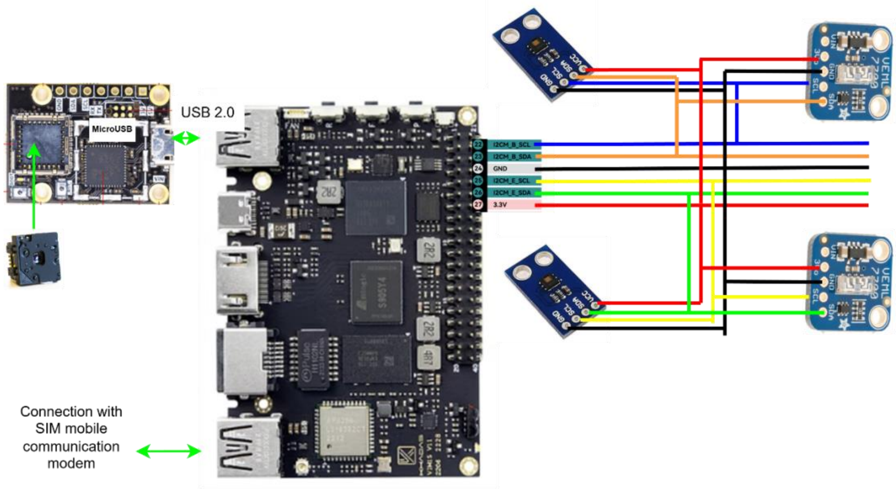

Fig. 3.1. Electrical circuit diagram.

As a result, the assembled prototype is placed in a casing for minimal protection of integrated circuits and the camera against the effects of air humidity in the greenhouse (Fig. 3.2).

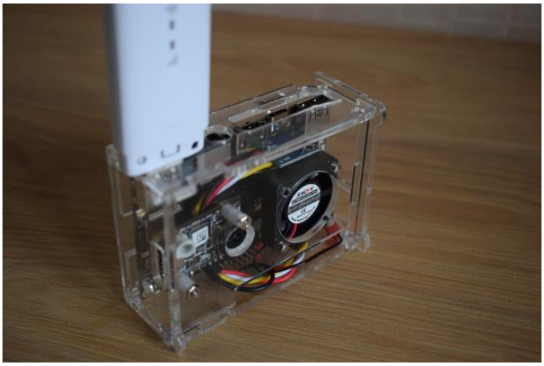

Fig. 3.2. Assembled prototype for data collection.

Data measurements were taken in a greenhouse (Fig. 3.3), where the conditions necessary for growth are provided either manually or automatically. The amplitude of temperature changes is limited and predictable, and there is minimal possible air flow and other factors that could temporarily affect the measurements taken, such as generating noisy data.

Fig. 3.3. Measurement collection at LBTU greenhouse.

Specifically, the observations in the greenhouse of the LBTU horticultural institute over two months (June 2024 to July 2024) were conducted in a greenhouse where various seedlings are prepared for outdoor planting. Several scripts are used for automated data collection, which are compiled in a GitHub repository (*https://github.com/ArtuursK/thermal-measurement-estimation*). The data collection script is run every 15 minutes using crontab commands. The script reads values from Khadas I2C buses using the smbus2 library. The library libuvc is used for obtaining thermal camera frames, allowing interaction with USB video class (UVC) devices. The OpenCV library is used for retrieving frames from the PureThermal module via USB.

The thermal radiation camera captures thermal images of plants every 15 minutes. Each image is saved as a 120 × 160 pixel 2D array in CSV format. The CSV format is chosen because Python allows processing files in this format without the use of additional external libraries. Although the thermal camera used is radiometric (calibrated values are provided in the camera's output channel), each pixel measurement has a manufacturer-specified accuracy of ±0.05 °C, and the camera can register temperatures ranging from –40 °C to +400 °C.

The VEML7700 light intensity sensor measures light intensity with approximately ± 10 % accuracy, ranging from 0 lux to 167 000 lux (lx).

The temperature and humidity sensor HDC1080 provided measurements of ambient temperature (with ± 0.4 °C accuracy and a range from –40 °C to 125 °C) and relative humidity (with ±2 % RH accuracy and a range from 0 % to 100 % RH).

Information about the measurement data set: Within two months (June 2024 to July 2024), a total of 1053 usable hourly measurements were obtained for each sensor (relative humidity, air temperature, light intensity), coinciding with automatically acquired thermal camera images.

- Air temperature:
    - max value: 38.01 °C;
    - min value: 10.46 °C;
    - average: 22.86 °C;
    - standard deviation: 4.91 °C.
- Relative humidity:
    - max value: 99.99 % RH;
    - min value: 37.9 % RH;
    - average: 88.60 % RH;
    - standard deviation: 15.80 % RH.
- Light intensity:
    - max value: 7952.5 lux;
    - min value: 0.0 lux;
    - average: 1828.94 lux;
    - standard deviation: 1684.49 lux.

3.2 Data analysis

During data collection, the author repeatedly encountered cases where sensors and thermal images lacked data for various reasons, such as sensor malfunctions or data transmission issues, which are not discussed in detail in this Thesis. These deficiencies are common in real environments and can cause inaccuracies in prediction results if not properly processed before model training. Therefore, an approach was chosen to group measurements by hourly averages for both sensor data and thermal images. This approach ensured a more complete dataset from the perspective of measurement frequency to compensate for incomplete measurements and improve the model's predictive capabilities (Kempelis et al., 2021b).

Data from each sensor was initially processed to eliminate missing values and inconsistencies. Thermal images and sensor measurements were normalized using the min-max normalization approach (Nuraisha & Shidik, 2018) to ensure a consistent scale among all image and sensor values prior to their use in prediction.

Since the collected thermal data had a time series nature (each thermal image was obtained every 15 minutes), similar to other sensor measurements, it was decided to explore potential relationships between the model input (thermal images) and output measurements (air temperature, relative humidity, soil moisture level, light intensity). To learn about the interrelationship of different measurements, correlation analysis of the measurements was performed before model training (Senthilnathan, 2019). Correlation was conducted both between collected sensor measurements (Fig. 3.4) and between thermal camera pixel temperature values and sensor measurements (Fig. 3.5). After the measurements, a correlation matrix was created (Fig. 3.4), which showed a high correlation between air temperature and light intensity measurements.

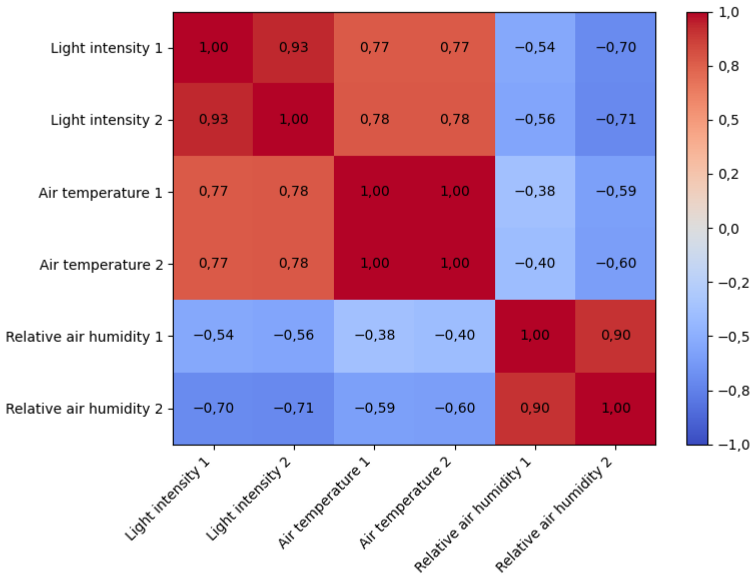

Fig. 3.4. Correlation analysis after measurements in 2024.

The initial analysis of the collected data characterizes the relationship of the collected data with the thermographic image, such as in correlation analysis. In this analysis, each pixel in the thermal images was evaluated in terms of how it correlates with other sensors (light, temperature, and humidity, as well as soil sensors) during data collection.

The results of the correlation analysis confirmed that thermal images closely correlate with the data from nearby air temperature sensors. Meanwhile, the correlation maps shown in Fig. 3.8 illustrate the interrelationship between pixel values and various sensor measurements. The axes of each correlation map reflect the 120 × 160 pixel coordinates corresponding to the dimensions of the thermal image frame. For example, in Fig. 3.5 (a), the pixel located at the 0 vertical and 0 horizontal coordinates (X = 0; Y = 0) appears in a darker zone, indicating a relatively high correlation with air temperature measurements compared to other pixels in the image. This is evidenced by the correlation coefficient exceeding 0.5, as seen on the adjacent correlation scale. It is essential to emphasize that these heatmaps reflect a two-month correlation analysis, where pixel values are compared with the respective time series data on air temperature, relative humidity, and light intensity, measured simultaneously. After collecting measurements in the greenhouse of the LBTU (Latvian University of Life Sciences and Technologies) Horticultural Institute from the beginning of June to the end of July, the correlation of thermal camera pixels with sensor measurements was analyzed (Fig. 3.5).

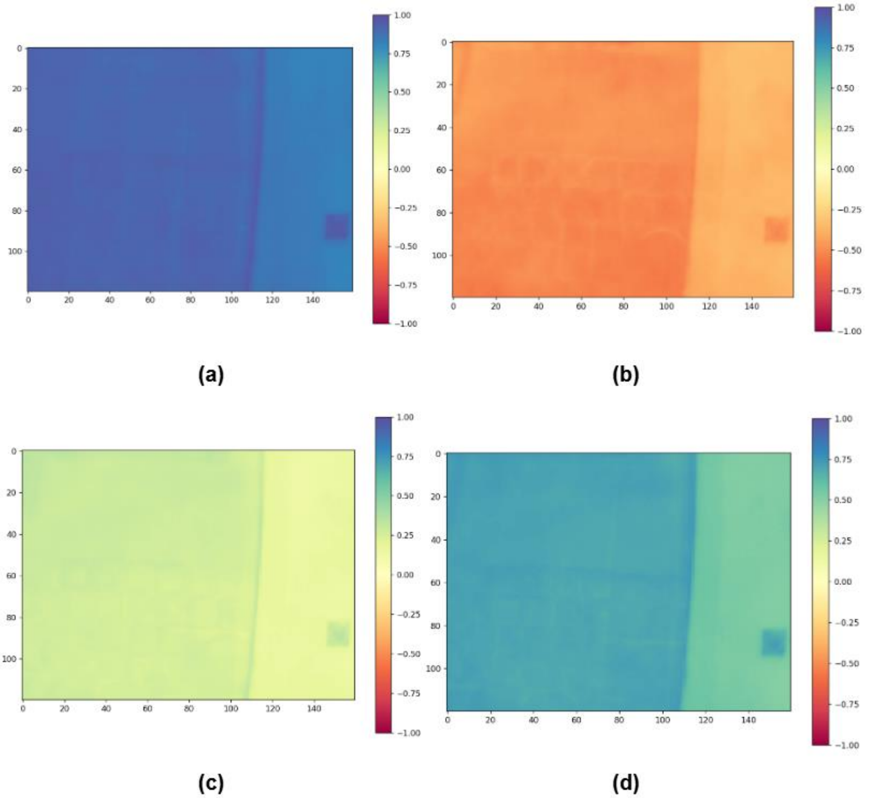

Fig. 3.5. Correlations with thermal camera image pixels during the data collection period in 2024. The correlation map is created between the thermal camera temperature pixel values and (a) air temperature sensor measurements, (b) relative air humidity sensor measurements, (c) calculated plant moisture sufficiency measurements, and (d) light intensity sensor measurements.

The sufficiency of moisture levels is calculated using measurements of air temperature, relative humidity, and leaf surface temperature. This method is found in several studies and is used to determine plant moisture-induced stress (Guebsi et al., 2024; Katz et al., 2023) and is a relatively more accurate method for determining moisture level sufficiency in plants than capacitive type sensors, as it includes additional environmental information. Capacitive-type sensors were used during the data collection for this Thesis in 2023 to measure moisture levels only in the soil, and they are subject to frequent calibration needs (Abdelmoneim et al., 2025).

3.3 Development of measurement estimation models

In the framework of this Thesis, a prototype module based on deep learning and computer vision was developed for predicting and more accurately assessing microclimate sensor measurements of strawberry (*Fragaria x ananassa 'Flair'*) and raspberry (latest selected hybrids from 2024 breeding) plant seedlings, using measurements collected over four months (July and August 2023, as well as June and July 2024) from various types of sensors.

This study investigates light intensity, relative humidity, temperature, and soil water content, as these factors significantly affect canopy temperature, which is visible in thermal radiation images. Light intensity promotes photosynthesis and the opening of plant stomata, increasing transpiration and ensuring leaf cooling. High relative humidity levels increase the risk of plant diseases. Soil moisture levels provide or limit the cooling effect, where sufficient soil water content helps keep leaves cool, while a moisture deficit causes leaf warming.

3.3.1 Development and training of the CNN model

Considering the sensor measurement prediction methods discussed in the studies by Maskey et al. (2020) and Ham et al. (2019), which have shown relatively high accuracy using the “VGGnet” type convolutional network architecture (Chandrapu et al., 2022), a configuration of this model's architecture was developed for deployment on the prototype. The used architecture is intended for image analysis, with the extraction of a single value (measurement) at the model's output. The input of the developed model is intended to use radiometric 120 × 160 pixel temperature matrices generated by thermal cameras, obtained from frames captured by the thermal camera.

In the initial training process, an NVIDIA GeForce GTX1060 GPU with 6GB graphics memory was used. The training utilized the mean squared error (MSE) loss function with the AdamW optimizer. The training cycle marks both the training and validation mean squared error after each epoch. Error metrics were visualized for each measurement initially at 100 epochs (Fig. 3.6) to determine overfitting or underfitting.

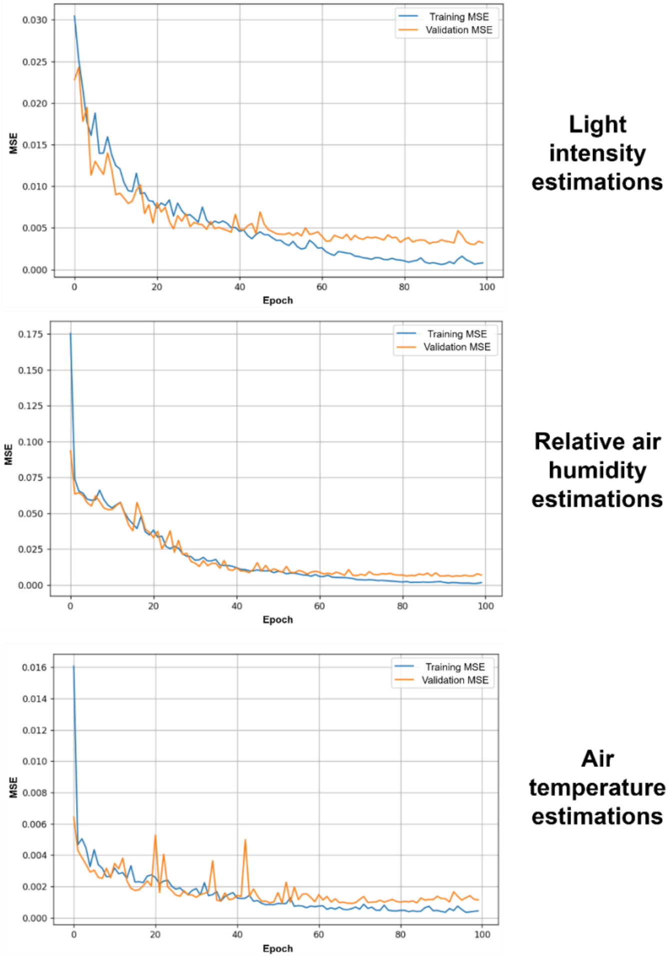

Fig. 3.6. Training error of air temperature, relative humidity, and light intensity at different epoch counts during CNN training.

The comparison of training and validation errors is necessary to evaluate model performance. The training error is calculated from the portion of the dataset used to adjust the model's parameters. The training error indicates how well the model's predictions match the data it has already used in the training process. It is expected that as the number of epochs increases, the error decreases with slight fluctuations that characterize the model's optimization process. In this case, the validation error is determined by a separate dataset that the model has not "seen" or used and serves as an indicative measure of the model's generalization ability (as opposed to overfitting). If only the training error were used to determine how long to train the model, it could lead to overfitting, where the model becomes too tailored to specific training data. On the other hand, if only the validation error were used without the training error, it would also not be possible to accurately determine the model's training dynamics, as the validation error may increase due to inappropriate training speed configuration or other parameters, which are relatively difficult to identify without a training error to compare against.

- Insufficient training (underfitting) is characteristic of the initial epochs, where training and validation errors are relatively large.
- Optimal model generalization is characteristic of the middle section, where the training error continues to decrease, but the validation error reaches a global minimum, or the curve flattens out.
- Overfitting is characteristic in cases where the training error decreases, but the validation error begins to increase after leveling, which can be explained by the fact that the reduction in training error no longer affects the reduction of validation error, or the prediction model "does not match" the data not used in training.

Therefore, the choice of the number of epochs corresponding to the minimum validation error is accepted as the model's generalization optimum. By examining the obtained results (Fig. 3.6), it can be concluded that the most suitable number of epochs for evaluating each measurement in the convolutional network model is:

1) air temperature: 40 epochs;
2) relative humidity: 60 epochs;
3) light intensity: 50 epochs.

After which, the training error stabilizes and no significant improvement in model performance occurs.

3.3.2 Development and training of the ViT model

For the implementation of the vision transformer model, the PyTorch open-source deep learning framework and the VitTiny model ("*vit_tiny_patch16_224*") were used, which is the original vision transformer configuration with a smaller number of parameters from the *timm* deep learning model library (Wightman, 2022), suitable for the spatial size of the thermal images used in this Thesis – 120 × 160 pixels. "*patch16*" indicates that the image is divided into non-overlapping 16 × 16 pixel blocks before being transformed into transformer tokens, while "*224*" in the name denotes the pixel length of the image edge with which this variant of the transformer architecture configuration was originally trained. The weights of the "*vit_tiny_patch16_224*" model were initially trained with input images with a resolution of 224 × 224 pixels. If the input size changes (differs from the original model), then the differences need to be interpolated, which may slightly affect the model's performance. In this case, from

120 × 160 pixels, the shorter edge – 120 pixels does not divide by 16 (the size of the block separated from the image), therefore it is necessary to interpolate an additional 8 pixels, resulting in an input size of 128 × 160 (Touvron et al., 2021).

After training the model, by examining the obtained results (Fig. 3.7), it can be concluded that the most suitable number of epochs for each measurement in the vision transformer model is:

1) air temperature: 10 epochs;
2) relative air humidity: 45 epochs;
3) light intensity: 75 epochs.

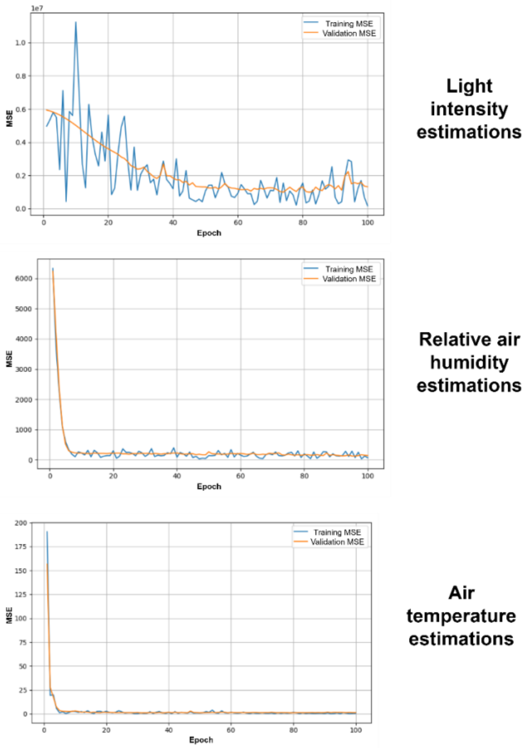

Fig. 3.7. Training error of air temperature, relative humidity, and light intensity at different numbers of epochs during ViT-Tiny training.

3.3.3 Development and training of the CvT model

Preparation of the convolutional vision transformer model included cropping the image to 112 × 112 pixels. This was done because the applied *ConViT_Tiny* architecture from the *timm* library transforms the image into a sequential string of tokens using a single two-dimensional convolution. This means that the width and height dimensions of the input image for the architecture must match. Considering that in this scenario the plants are located on the left side of the thermal image, 112 × 112 pixels were taken from the top left corner to preserve as much information as possible necessary for measurement estimation. Error indicators were visualized to determine overfitting or insufficient model training (Fig. 3.8).

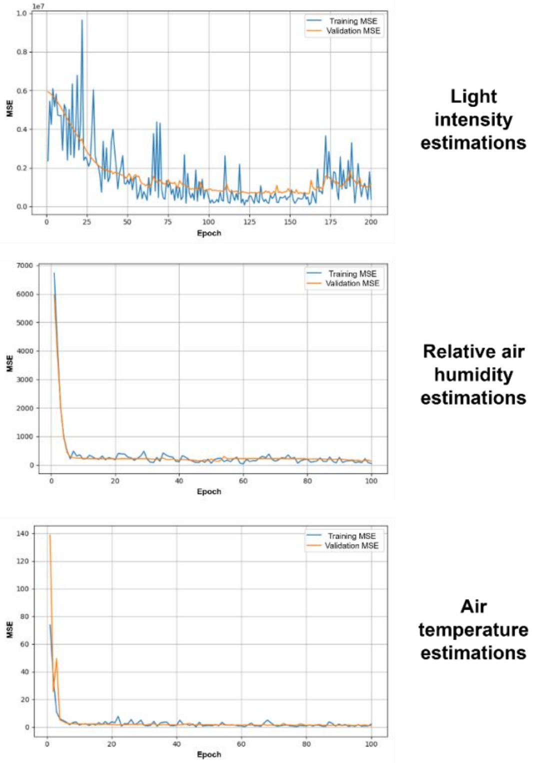

Fig. 3.8. Training error of air temperature, relative humidity, and light intensity at different epoch counts during the training of the ConViT-Tiny vision transformer.

By examining the obtained results (Fig. 3.8), it can be concluded that the most suitable number of epochs for training each measurement in the convolutional vision transformer model is:

1) air temperature: 10 epochs;
2) relative air humidity: 45 epochs;
3) light intensity: 160 epochs.

After which, there is no significant improvement in model performance during training.

4. DEVELOPMENT AND VALIDATION OF MEASUREMENT ASSESSMENT APPROACHES

Within the framework of the Thesis, an approach is being developed based on the previously constructed data collection module, its collected measurements, and the application of the most suitable model for measurement estimation. To validate the developed approach, the most appropriate model performance estimation metrics are determined, and the results of the obtained measurement estimation models are compared with the real measurements of measuring devices or sensors to ensure the reliability of the model results and assess errors.

4.1 Development of approach

The approach developed within the framework of the Thesis provides for automated collection, processing, and estimation of plant environment measurements in greenhouses or other places where monitoring of microclimatic conditions is essential in the context of precision agriculture. For the automation of measurement estimation, data streams generated by multiple measurement sources – environmental or microclimate sensors and thermal radiation sensors – are used. The approach is based on data acquisition for training a machine learning model, where measurements of air temperature, relative humidity, and light intensity are taken and stored at 15-minute intervals. The 15-minute interval provides a compromise between data granularity and processing efficiency, and is therefore considered sufficient to capture significant temperature trends without significant information loss. Measurement values are stored in a database along with the date and time each measurement was taken. At the same interval, thermal camera measurements or frames are also collected, which are saved as separate files (.csv format) with the date and time in the file name and a two-dimensional temperature pixel matrix in the file content.

Both individual sensor measurements and thermal camera frames require preprocessing, which includes determining concurrent values. Concurrent values are measurements that match (in time) both the individual sensor measurements (air temperature, relative humidity, light intensity) and the frames obtained from the thermal camera. To maximize matching measurements and obtain as much training data as possible, within the experiment, the data is grouped by hour with an average value for each hour. Records that lack matching thermal measurements or thermal measurements without matching sensor measurement records are discarded or not considered in the machine learning model training, as the study does not address the prediction or estimation method of time series regression measurements.

To ensure continuous and autonomous model learning, the measurement estimation model training process is automatically initiated once a day (when the microclimate monitoring processes are least busy) to obtain measurement estimations and errors. The model's performance is classified as sufficient or insufficient by comparing it with the actual sensor measurements during the corresponding time period. This is necessary to reduce errors and ensure the model can adequately generalize for measurement estimation. The overall flowchart of the approach is given in Fig. 4.1.

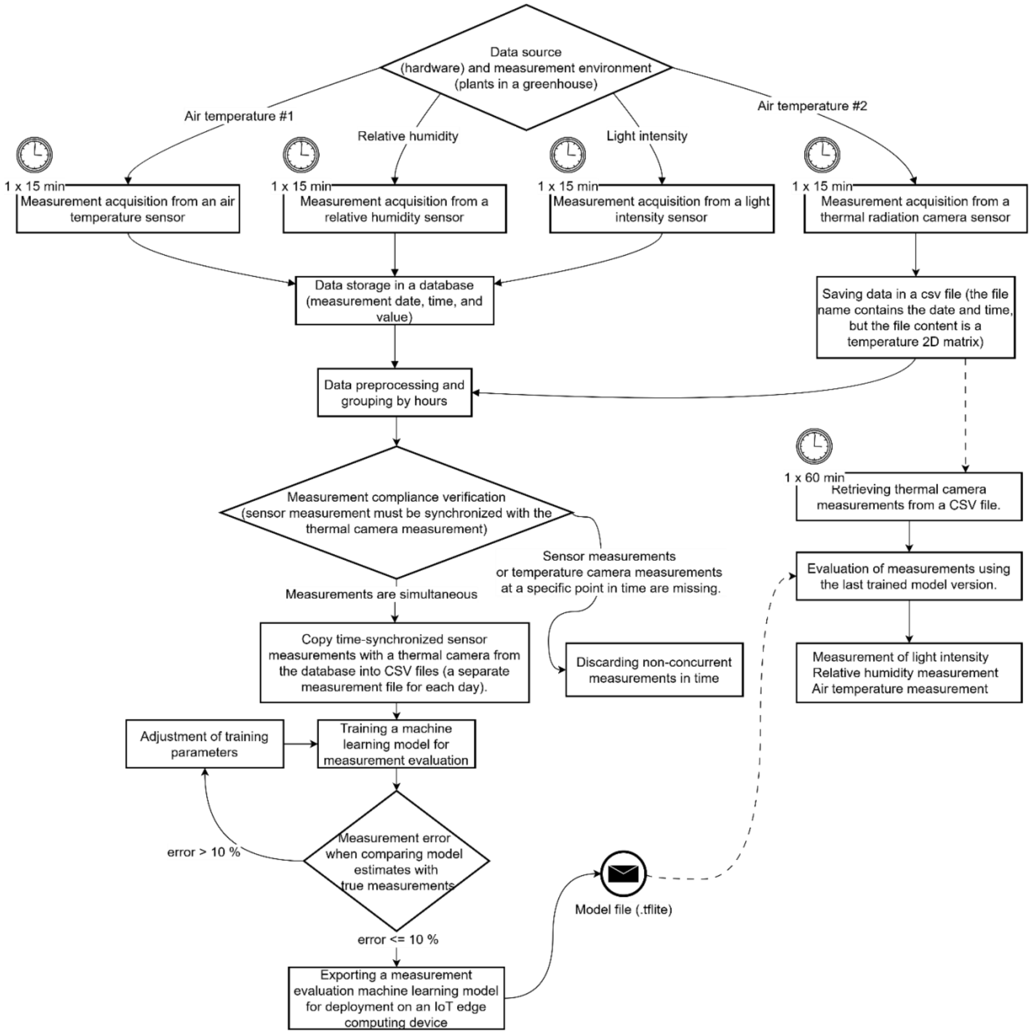

Fig. 4.1. Flowchart of measurement estimation approach.

The training of the models mentioned in the approach can be carried out both on edge computing devices simultaneously with the data collection process, and using high-performance computing hardware.

4.2 Prototype development

A prototype related to the previously developed measurement assessment approach includes an automated microclimate measurement collection module and a data processing and analysis module using thermal cameras and microclimate sensor measurements. The prototype is intended as a practical solution that combines the functionality of data collection, analysis, and machine learning modules into a unified platform, providing real-time measurement assessment. To determine the most suitable architecture to deploy in prototype devices, a series of experiments were conducted using various model architectures – convolutional networks, vision transformers, and a convolutional vision transformer hybrid architecture. The results of the experiments influence the prototype development strategy when selecting the main model architecture for edge computing applications in precision agriculture. Technically, the prototype includes an IoT edge computing device with an integrated thermal camera module, local data processing and storage software, as well as a web application for real-time monitoring and user interaction. The prototype devices are intended to operate autonomously, periodically collecting data and processing it locally, thereby reducing dependency on cloud services and ensuring system operation under limited connectivity conditions.

The planned prototype implementation involves its integration into the existing agricultural IoT infrastructure, ensuring compatibility of open hardware and open software with other sensors and control devices. This allows the system to be scaled and adapted to the requirements of different greenhouses or field areas, while maintaining data security and privacy aspects.

4.3 Experiment plan and description

Before evaluating measurements based on the prototype development approach, it is necessary to conduct experiments for measurement estimation. The experiments are implemented as a complex of experiments, consisting of the training of three machine learning models differing in architecture.

Statement of the problem under investigation. Comparison of measurement estimation models and analysis of their performance.

Model of the system being studied.

Input – thermal camera images or temperature matrix.

Factors that can affect the output: model architecture, hyperparameters (training speed, number of training iterations, batch size), input image size (coordinates).

Output – measurement estimation and its correspondence to the actual sensor measurement.

Experimental plan

1. Using the developed data collection prototype and automated script, collect measurements.
2. Prepare and process input data (temperature measurement frames) for training machine learning models, according to the model architecture specifications.
3. Train computer vision regression models and compare their accuracy.
4. Repeat the training process of each model multiple times to ensure the stability and reproducibility of the obtained results.
5. Summarize and analyze the obtained results.

To execute the experimental plan, a series of experiments is planned, containing four main experiments. The description and objective of each experiment are given in Table 4.1.

Table 4.1

Planned Measurement Estimation Experiments

No.	**Experiment description**	**The aim of the experiment**
1.	Using a convolutional network architecture and the dataset obtained in 2023, three convolutional models were trained. Training was repeated several times, and the grid search hyperparameter optimization method was used to find the highest possible accuracy model configuration.	Determine the optimal model configuration of convolutional networks and the accuracy of models in the assessment of measurements (soil moisture, relative air humidity, and light intensity).
2.	Using a convolutional network architecture and the dataset obtained in 2024, three convolutional models were trained.	Determine the accuracy of convolutional network models in the estimation of measurements (air temperature, relative humidity, and light intensity).

No.	Experiment description	The aim of the experiment
3.	Using a vision transformer architecture and a dataset obtained in 2024, three vision transformer models were trained.	Determine the accuracy of vision transformer models in the estimation of measurements (air temperature, relative humidity, and light intensity).
4.	Using the convolutional vision transformer architecture and the dataset obtained in 2024, three convolutional vision transformer models were trained.	Determine the accuracy of convolutional vision transformer models in the assessment of measurements (air temperature, relative humidity, and light intensity).

Experiment objective: Determine which of the three selected and trained machine learning models allows for measurement estimation with relatively higher accuracy and can be used for implementing the estimation approach in the prototype. Using the collected dataset, three different machine learning models were trained. The models were developed with the purpose of evaluating measurements – light intensity, relative humidity, and air temperature (Table 4.2). The number of epochs was obtained from the model validation study previously examined in the study.

Table 4.2

Models Trained in Measurement Estimation

	1. Set of models (CNN, ViT, CvT)	**2. Set of models (CNN, ViT, CvT)**	**3. Set of models (CNN, ViT, CvT)**
Model input	Thermal camera image matrix 120 × 160 pixels (°C)	Thermal camera image matrix 120 × 160 pixels (°C)	Thermal camera image matrix 120 × 160 pixels (°C)
Model output	Light intensity (Lux)	Relative air humidity (%)	Air temperature (°C)
Hyperparameters	Training speed: 0.001 Batch size: 16 Epochs: (CNN: 50, ViT: 75, CvT: 160)	Training speed: 0.001 Batch size: 16 Epochs: (CNN: 60, ViT: 45, CvT: 45)	Training speed: 0.001 Batch size: 16 Epochs: (CNN: 40, ViT: 10, CvT: 10)

4.4 Overall assessment of model accuracy

To assess the feasibility of measurement estimation based on thermal images, models were trained in several iterations using a regression-appropriate loss function – mean squared error (MSE), which is often used to show the difference between predicted or estimated values and actual measurement values (Naznin & Islam, 2023).

The VGG-based CNN model demonstrated relatively the highest accuracy among all three models used (RMSE = 2.29 °C, 0.075 % RH, 0.059 lux; $R^2 \geq 0.897$) over 40–60 epochs. This indicates that for the given dataset, it offers the most stable and accurate possible alternative in such a scenario. Meanwhile, ViT-Tiny and CvT-Tiny, although competitive in assessing temperature measurements, showed larger errors in evaluating humidity and light intensity measurements.

Considering the relatively lower accuracy results of transformer models and the dataset volume (1053 measurements), it was decided to repeat experiments with different training data without changing the number of epochs. In the repetition of experiments, the cross-validation method was used, changing the training and validation set samples in each experiment. Additionally, within the framework of the experiments, model training was repeated using the K-fold cross-validation approach to ensure an objective performance estimation of the models. Furthermore, it was necessary to use stratified K-fold cross-validation because, in the training of the light intensity estimation model, it would be important for each training set to contain both high and low light intensity measurements (reflecting the daily cycle in the data).

In order to objectively compare model performance, an analysis of model training performance with varying training data volumes was conducted. For example, among all light intensity estimation models (Fig. 4.2), it was observed that all models show a consistent RMSE reduction as the proportion of training data increases, indicating an improvement in estimation accuracy with an increase in the size of the training dataset.

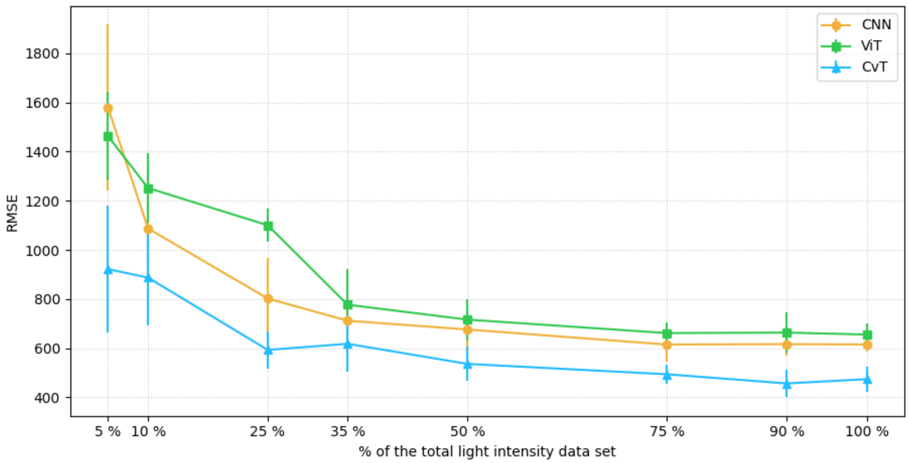

Fig. 4.2. Comparison of training models for light intensity estimations.

For interpretation of results, the maximum value of light intensity measurements is 7952.5 lux, the minimum value is 0.0 lux, the average value is 1828.94 lux, and the standard deviation is 1684.49 lux. Thus, the most significant reduction in model errors is observed in the range from 5 % to 35 % of the total dataset, after which the reduction in model errors stabilizes, indicating that the dataset addition might not provide a significant improvement in accuracy for all three models. Among the models, CvT achieves the lowest RMSE in all cases.

Similar observations were made when evaluating relative humidity in model comparisons (Fig. 4.3), where CvT achieves the lowest RMSE in all cases for each part of the dataset. The ViT model achieves relatively weaker results and stabilizes later than the other models.

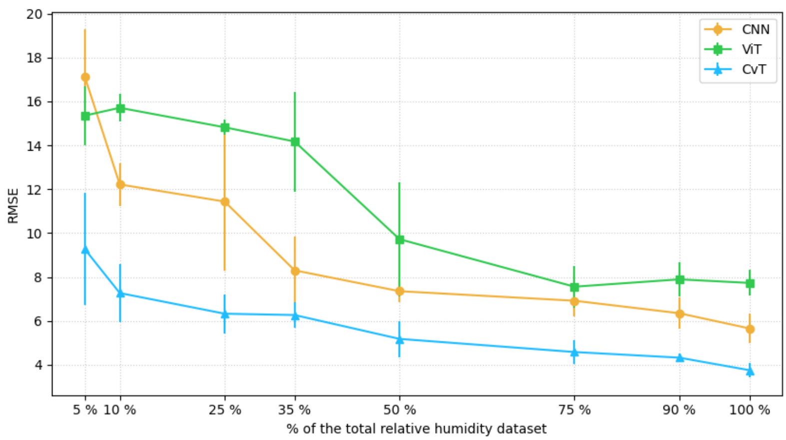

Fig. 4.3. Comparison of training models for relative humidity estimations.

Slightly different results were obtained in the comparison of air temperature estimation models, where the CvT model shows the lowest RMSE, indicating high generalization ability and efficiency in using training data (Fig. 4.4). The ViT model shows mediocre performance, with a stable error reduction as the data volume increases, while the CNN model maintains the largest RMSE error and stabilizes relatively slower than the other models. Overall, the CvT model demonstrates the highest ability to effectively learn from a limited amount of data while maintaining stable performance using the full dataset.

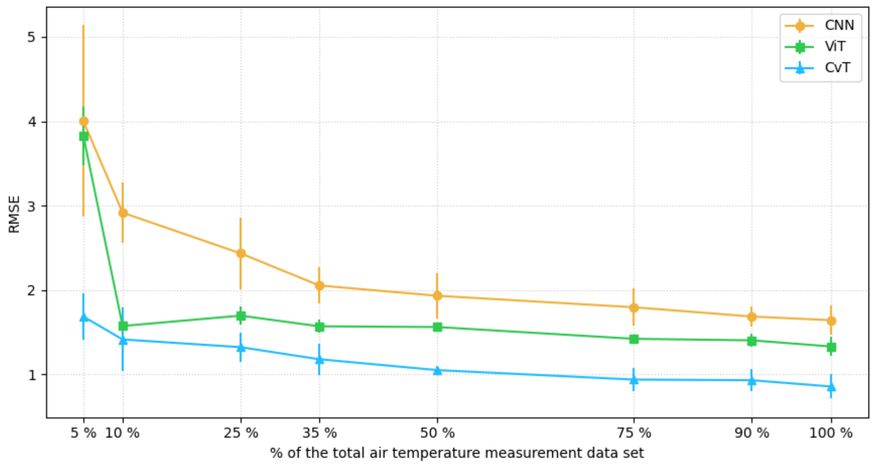

Fig. 4.4 Comparison of training models for air temperature estimations.

As a result, in all comparisons, it is also possible to identify points where increasing the volume of the dataset no longer provides a significant increase in accuracy, indicating data sufficiency for stable model generalization ability.

After repeating experiments and applying cross-validation methods, the comparison of both transformer models indicates that CvT shows higher accuracy than ViT for all three measurement types (light intensity, air temperature, relative humidity). The greatest improvement differences are observed in light intensity and relative humidity predictions, where error reduction and R^2 increase are significant. In the case of temperature, both models demonstrate equally high accuracy, but CvT maintains an advantage with lower error and a higher determination coefficient. The results suggest that the integration of convolutional elements into the transformer architecture enhances the model's ability to evaluate the given measurements.

The obtained results are summarized and compared with other error metrics (Fig. 4.5).

CvT demonstrates the highest accuracy, determined by the lowest MAE and RMSE metrics and the highest coefficient of determination, indicating a relatively close relationship between thermal images and temperature measurements. The ViT model has larger errors but still maintains a high R^2, whereas the CNN falls behind both in terms of error magnitude and R^2. The standard deviations observed among the models are small.

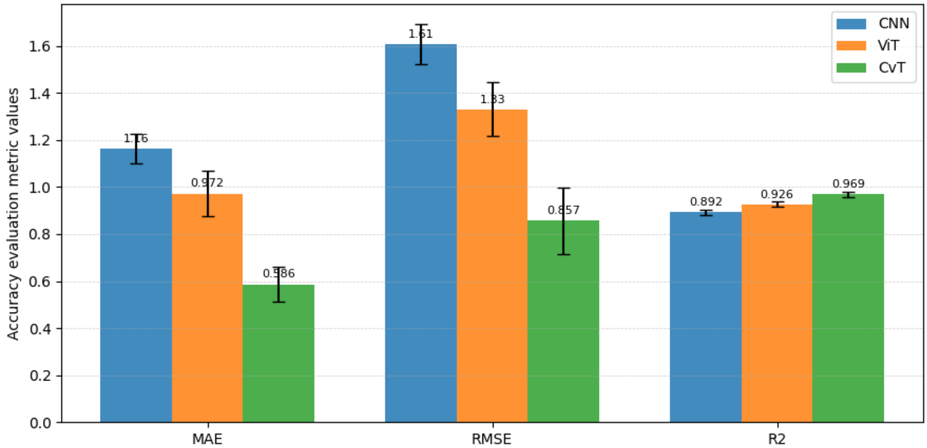

Fig. 4.5. Error and accuracy metrics for air temperature estimation models.

In the estimation of relative humidity (Fig. 4.6), CvT unequivocally outperforms the other models, having significantly lower MAE and RMSE and higher R^2, with less variation between folds, indicating relatively better generalizability. CNN ranks second in accuracy and achieves relatively higher precision than ViT, whose errors are higher, and R^2 is lower.

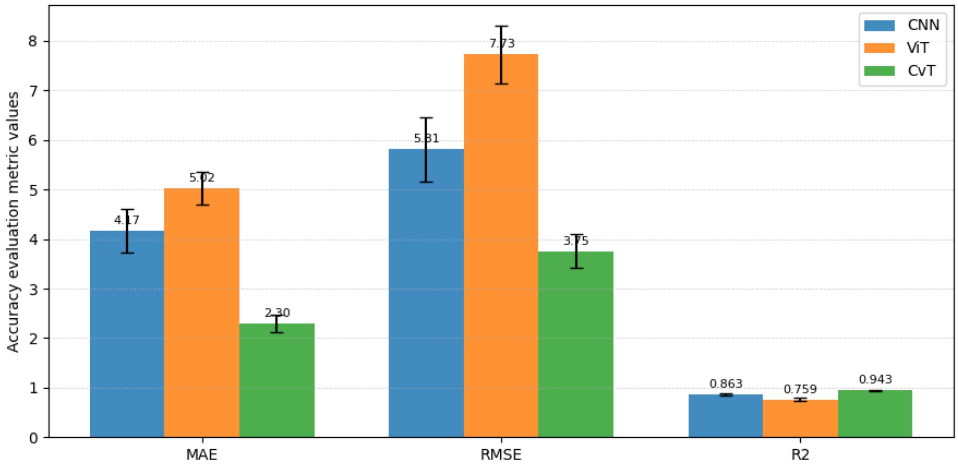

Fig. 4.6. Relative humidity error and accuracy metrics for estimation models.

In the assessments of light intensity (Figs. 4.7 and 4.8), CvT is the comparatively best model (with the lowest MAE/RMSE and highest R^2 coefficient). CNN slightly surpasses ViT, achieving a higher R^2 and smaller errors. The standard deviation models are relatively moderate, indicating sufficient stability between cross-validation folds.

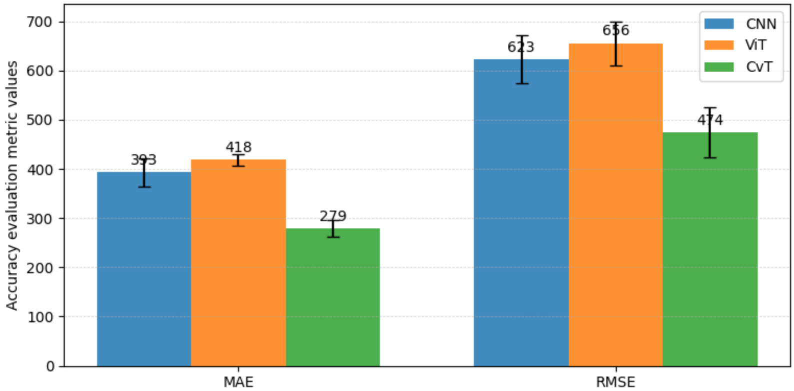

Fig. 4.7. Comparison of MAE and RMSE for light intensity estimation models.

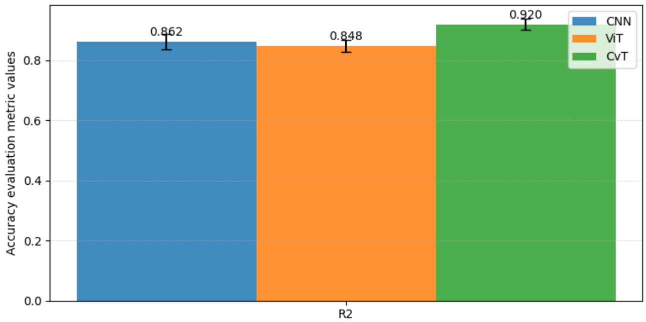

Fig. 4.8. R^2 comparison of light intensity estimation models.

Overall, the performance of CvT dominates the estimation across all three measurements. These results generally confirm that transformer architectures, enhanced with CNN features, can achieve the highest accuracy in thermal image regression even when using a relatively small dataset during the training process. However, to further ensure the stability of hybrid convolutional transformer performance after model training, comparatively higher accuracy fold models were selected and tested for noise resilience in images from all models. This was done to simulate noisy data at model input, which could arise due to various external conditions or the wear and tear of the thermal radiation sensor, potentially causing inaccuracies in the collected data (Juan et al., 2024). One way to simulate sensor wear is to use Gaussian noise

(Chowdhury et al., 2017). Gaussian noise characterizes measurement errors whose values derive from a normal or Gaussian probability distribution with a mean value of 0 and a specified standard deviation. For conducting experiments, artificially created thermal image datasets with varying levels of noisiness were generated using a Gaussian filter. Each pixel value is independently altered using this noise, which characterizes slight fluctuations around the true measurement, such as those caused by the sensor's thermal noise (Wantao et al., 2025). In thermal images, Gaussian noise with a standard deviation σ creates approximately ±σ °C uncertainty for each pixel used in the creation of noisy data sets (Fig. 4.9).

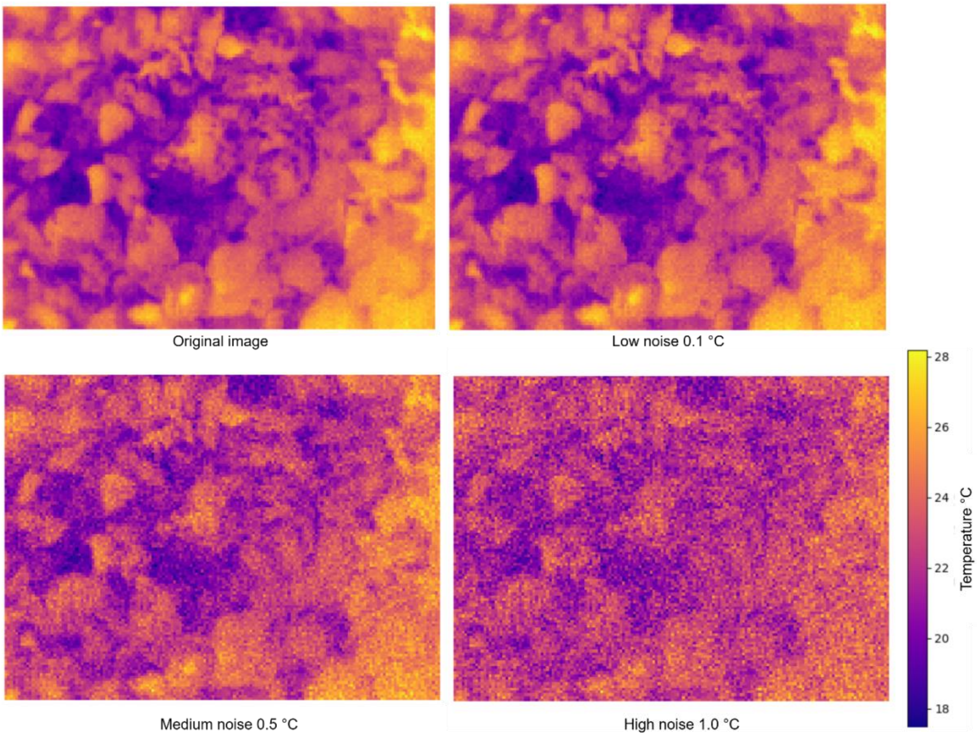

Fig. 4.9. Example of noisy data at different levels.

Analyzing the results, it can be concluded that the CNN model has relatively greater resilience against noisy input data, evaluating two out of three measurements, namely light intensity and relative humidity (Fig. 4.10).

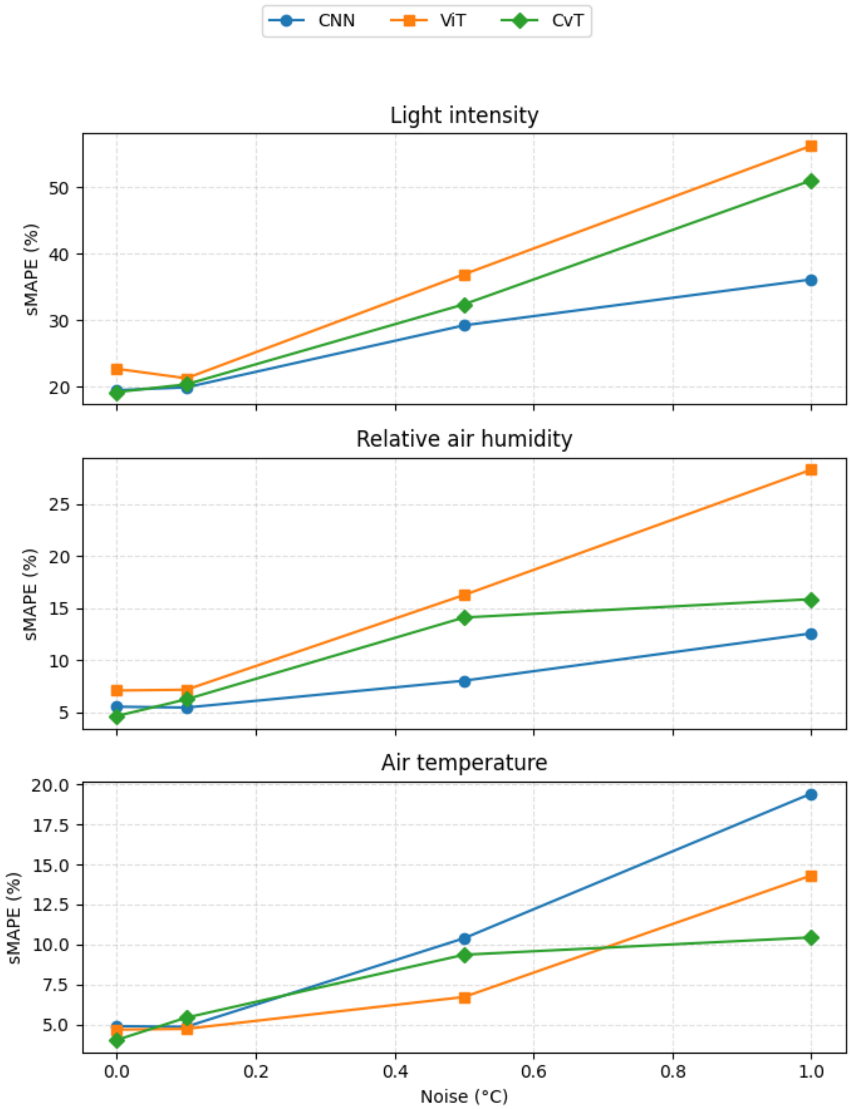

Fig. 4.10. Comparison of models at different noise levels for each type of measurement.

The CNN model maintained the lowest relative error for both light intensity and relative humidity, with a slower SMAPE increase as noise levels rose, indicating the convolution architecture's resilience to noise increase. The convolutional vision transformer retains relatively higher resilience to noise increase in images.

4.5 Approach implementation methodology

In order to utilize the results obtained from the study and to practically implement the developed approach in agricultural plant monitoring processes, the methodology for implementing the approach is offered in the Thesis. Considering the IoT network architectures revealed in the literature analysis, which are successfully applied in agriculture, the methodology is primarily based on integrating the approach into existing agricultural IoT networks. The components of the approach developed in this Thesis include a measurement estimation device (which can also be multiple devices) placed in the greenhouse environment, a machine learning model for measurement estimation located in the device, scripts for running the model and collecting data from the device's thermal camera module, as well as a web application for local and inter-device communication.

The methodology for implementing the mentioned measurement estimation approaches includes the following stages:

- definition of measurement estimation guidelines;
- conceptual model development (defining resources, structure, parameters, and other attributes or components);
- defining IoT components;
- definition of functional guidelines;
- integration of devices and components (communication networks, deployment methods, data storage methods, and used devices);
- user interface development.

Aspects of information and data security in the development of access implementation methodology are intended to use widely known and accepted industry guidelines, therefore they are not separately described within the scope of this work.

RESULTS AND CONCLUSIONS

Results of the Thesis research

A comprehensive analysis of scientific literature on the use of IoT sensors and computer vision technologies in precision agriculture was conducted.

A prototype data collection module based on open-source and open-hardware solutions was developed. Measurements were collected over a four months (July–August 2023 and June–July 2024), resulting in a total of 6592 radiometric thermal images (120 × 160 pixels) and 4860 microclimate measurements (air temperature, relative humidity, soil moisture, and light intensity).

A correlation analysis was conducted between thermal image pixels and microclimate measurements. The results of the correlation analysis indicated an interrelationship between several individual measurements. The results showed a high positive correlation with air temperature ($r = 0.9$), a medium negative correlation with relative humidity ($r = –0.5$), and a positive correlation with light intensity ($r = 0.77$).

Three deep learning models were developed and compared through several experiments: –a convolutional neural network, a vision transformer, and a convolutional transformer hybrid or convolutional vision transformer model for evaluating microclimate measurements from thermal images.

Comparative analysis of models revealed that the vision transformer model demonstrates relatively the highest accuracy in evaluating all measurements, achieving results with the original dataset:

- in air temperature estimations (RMSE = 0.86 °C, $R^2 = 0.969$);
- in relative humidity estimations (RMSE = 3.75 % RH, $R^2 = 0.943$);
- in light intensity estimations (RMSE = 474 lux, $R^2 = 0.920$).

The vision transformer model also maintained relatively high accuracy when trained on limited portions of the dataset.

The robustness and stability against noisy input data of all three high-precision trained models were systematically tested. As a result, the CNN model demonstrated the highest resilience to noise increase in thermal images for the estimation of light intensity and relative air humidity, showing a lower symmetric mean absolute percentage error compared to the convolution transformer model.

The results demonstrated a high correlation between the values of thermographic radiometric images and several significant microclimate measurements (air temperature, relative humidity, soil moisture level, light intensity). The performance of the models was validated using the cross-validation method, confirming stable result acquisition regardless of the training set sample.

A measurement estimation approach has been developed, a prototype based on it, as well as a description of the implementation methodology for integrating measurement estimation into precision agriculture IoT networks.

After summarizing and analyzing the obtained results, it can be concluded that both theses defined in the introduction of the Thesis have been confirmed.

1. Using the developed microclimate measurement estimation approach, which includes a convolutional vision transformer model, it is possible to obtain a measurement estimation that is relatively more accurate for relative humidity, light intensity, and air temperature sensor measurements than the basic convolutional or vision transformer models.
2. Using the trained convolutional vision transformer model for microclimate measurement estimation, it is possible to achieve 80 % or higher accuracy for relative humidity, light intensity, and air temperature sensor measurements.

Conclusions of the doctoral thesis

The prediction and estimation of measurements from image data have not been sufficiently described in international scientific publications, which also motivated the execution of this study. The most significant scientific contribution of this Thesis is the formulation of a new deep learning approach for evaluating microclimate measurements from thermal images, demonstrating the advantages and limitations of transformer and convolution architectures in noisy, limited data conditions in the context of precision agriculture.

Computer vision and deep learning methods enable effective estimation of microclimate measurements from thermal images, achieving high accuracy. The application of machine learning models allows for maintaining low plant monitoring costs and offers potential for integration into resource-constrained IoT devices.

Based on the developed prototype, it is possible to enhance an existing agricultural IoT network with thermal radiation and other types of visual sensing devices to analyze the collected data and continue improving the prototype's real-time measurement estimation.

The results provide a theoretical and practical basis for future solutions that will enable the replacement or supplementation of traditional sensor networks with thermal image analysis, significantly reducing data acquisition costs and energy consumption in IoT systems.

The new deep learning approach developed in the Thesis for evaluating microclimate measurements complements the knowledge of using indirect measurements in agricultural plant monitoring systems. A systematic comparison of models revealed that the hybrid CvT-Tiny architecture provides the highest accuracy in all three measurement estimation tasks, and is able to maintain this accuracy with a limited volume of the dataset used for training, which has not been researched until now. CNN models also maintain high accuracy in assessing relative humidity and light intensity, especially when noise occurs in input image data. Noise in data, in the context of precision agriculture, can be common due to various external conditions or device wear. This is one of the most significant scientific contributions of this study, as it shows that CNN models or CvT together with CNN architecture models would be relatively more suitable in the context of precision agriculture for sensor measurement estimations. Within the framework of the Thesis, it is quantitatively assessed how prediction uncertainty increases under the influence of noise in different architectures, thereby revealing differences in the performance of the latest architectures in the field of computer vision. It provides new theoretical insights into the advantages and limitations of transformer and convolution architectures depending on the volume of data, noisy data, and the task.

Unlike previous studies that focused on direct sensor data analysis or the use of a single architecture, this study performs a systematic comparison of three different deep learning models with a special emphasis on noise resilience and data limitations, which have not been thoroughly analyzed in the literature so far. These observations expand the theoretical understanding of the stability of transformer models and the peculiarities of their training dynamics in precision agriculture tasks. Overall, the study confirms that indirect assessment of microclimate parameters from thermal images is not only technically possible but also practically achievable with high accuracy. This marks a new direction in the development of precision agriculture, where smart visual systems become a full-fledged alternative to traditional sensors and open up opportunities for more economically efficient and sustainable data collection.

Research limitations

The limitations of the study are related to the relatively small and seasonally restricted dataset obtained from a specific constant location, as well as the fact that the tested architectures were adapted for the specific task rather than being created entirely anew. Among the limitations of this study, the characteristic feature of thermal camera measurements should be mentioned, i.e. it can directly capture only surface temperature. As is known, measurements of air temperature, light intensity, and relative humidity can be influenced by external factors such as air pressure, vapor pressure deficit, and others, whose impact on measurements is beyond the scope of this study. These limitations could be addressed in future studies by training models that include measurements collected over a longer period, noisy measurements, and additional known parameters at the location where the measurement estimation approach is used, such as shading, sunlight angle, reflection, or using meteorological station data on average air temperature, precipitation, wind speed, and air humidity in the region, and others. To ensure model generalizability, a broader dataset is needed, including different seasons, plants, and growing environments, and performing measurement estimations outside the greenhouse.

Future research directions

To more effectively justify the use of thermal imaging in microclimate measurement estimation, it is necessary to expand the data set across different seasons, regions, and also consider other crops and growing conditions (both in greenhouses and outdoors). This would allow for improved assessment of model generalization capabilities in various precision agriculture scenarios. The sensitivity of the transformer architecture to noise in images revealed in the study indicates the need to theoretically and practically analyze the impact of noisy data on model stability and training. Therefore, it might be worth exploring data augmentation strategies in transformer architectures, such as applying noisy data in model training or using multiple historical thermal image datasets for model training to assess a specific measurement, providing the machine learning model with a broader context for accuracy improvements. Based on the ability to predict microclimate measurements from thermal images, future studies should develop methodologies that combine thermal, spectral, and other types of images with direct measurement sensors. This would allow validating the superiority of measurement assessment approaches over other methods and expand knowledge about the interrelationships of various measurements. To enhance the theoretical value of the obtained results, it is necessary to study how the developed models work with other plants and in different climatic regions, as well as to formulate conditions under which the transfer of models ensures sufficient accuracy. In future research, it would be useful to develop models that allow the estimation of essential measurements such as light spectrum, vapor pressure, and others through the analysis of thermal images and other visual data. This approach would complement the theoretical framework for assessing microclimate measurements without the use of direct sensors.

INFORMATION SOURCES

The full list of information sources used in the Thesis can be found in the complete version of the Thesis.

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