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**SELECTION OF TECHNICAL MEANS OF COMPUTER VISION ACCORDING TO THE ANALYTIC HIERARCHY PROCESS**

The problem of real-time image recognition has great relevance and significance in various fields, providing fast and accurate recognition of objects in images, which is of great importance for further analysis and decision-making.

Calculation data:

- |                       |                      |
|-----------------------|----------------------|
| Selection criteria:   | Decision options:    |
| – Type of connection; | – Brio Ultra HD Pro; |
| – Resolution;         | – Depth Camera D435; |
| – Frames/sec;         | – Camera Module v1;  |
| – Megapixels;         | – Camera Module v2;  |
| – Viewing angle;      | – Camera Module 3;   |
| – Price.              | – Waveshare IMX219-  |

77.

To determine the optimal type of camera among 6 options according to the specified criteria, the analytic hierarchy process applied. The hierarchical structure

$$A = \begin{pmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1/5 & 1/5 & 1/3 & 1/3 & 1/7 \\ 5 & 1 & 3 & 6 & 3 & 1/6 \\ 5 & 1/3 & 1 & 6 & 5 & 1/7 \\ 3 & 1/6 & 1/6 & 1 & 1 & 1/7 \\ 3 & 1/3 & 1/5 & 1 & 1 & 1/5 \\ 7 & 6 & 7 & 7 & 5 & 1 \end{pmatrix}$$

Microsoft Excel spreadsheet processor was used to compare objects according to each of the criteria. The global priority for each type of camera is calculated according to the formula:

$$A = \sum_{i=1}^n k_i w_i,$$

where  $k_i$  is the criterion priority vector;

$w_i$  is the priority vector of the object according to each criterion.

The calculation results are summarized in Table 1.

Table 1 – Global priorities

Camera name	Global priority
Raspberry Pi v1	0,1725
Raspberry Pi v3	0,2641
Waveshare	0,3137
Raspberry Pi v2	0,2469

depicted in Figure 1 includes the objective, criteria, and alternatives.

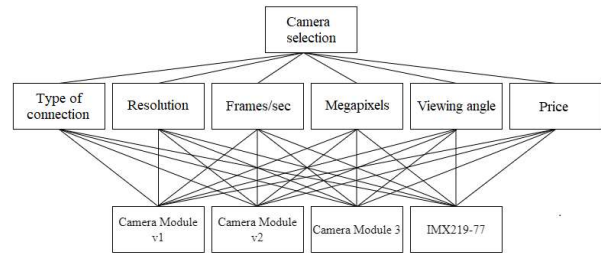


Fig. 1 – Hierarchical structure

According to Saati's scale of relative importance [1], priorities were determined and a matrix was formed, where the relative importance of parameters  $a_{ij}$  characterizing the weight of judgments is compared in

$$\text{pairs } \frac{\omega_i}{\omega_j} = a_{ij}.$$

According to the results of calculations using the analytic hierarchy process, the optimal type of camera for the computer vision system was determined.

References

1. Saaty T.L. Relative measurement and its generalization in decision making why pairwise comparisons are central in mathematics for the measurement of intangible factors the analytic hierarchy /network process, 2008.

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**EMBEDDED SYSTEM DESIGN  
TECHNOLOGIES FOR AI-DRIVEN SMART  
LIGHTING**

The rapid advancement of energy-efficient technologies, automation, and artificial intelligence (AI) is transforming various industries, including the development of intelligent lighting systems. These innovations are driven by the need to enhance energy efficiency, lower costs, improve user comfort, and implement automated, adaptable solutions across different environments. These systems are integral to a wide range of applications, from residential homes to commercial spaces and even public infrastructure like street lighting.

In connection with the growing demand for energy saving, the development of intelligent lighting systems is encouraged. These systems include components such as light sources, lamps, sensors, control units and connection elements. The development process involves several key stages. In the first stage, the embedded level, the lighting mechanism is developed, which typically consists of an LED chip mounted on a printed circuit board. This board contains the electrical and mechanical connections and is the backbone of the smart lighting system. The second layer integrates luminaires and other lighting systems to provide functional lighting solutions for a variety of applications, including human-centric lighting. The third level provides energy management, through which control of energy use, optimization of natural lighting and the possibility of remote control are achieved. Finally, the fourth layer adds connectivity by introducing automation features such as remote control, presence detection and lighting optimization [1].

Standardized communication protocols are used to ensure communication between the various components, which are listed below. The Digital Addressable Lighting Interface (DALI) protocol is used for building automation. Digital Load-Side Transmission (DLT) protocol designed only for lighting control. The digital multiplexing (DMX) protocol is used in entertainment applications and stage lighting. The Digital Serial Interface (DSI) protocol provides easy control of up to 100 devices per controller with minimal programming [1].

Intelligent lighting systems controlled by AI are able to adapt to user behavior, schedules and preferences, creating a more personalized and adaptive environment. For example, AI systems automatically dim or turn off lights when there are no people in the room, adjust brightness according to the time of day, which leads to energy savings. Despite these advantages, there are still some challenges, including privacy and implementation costs. AI-based systems require constant data collection to personalize lighting settings, which raises concerns about data security and user privacy. In addition, the initial setup and infrastructure investment may be prohibitive for some users [2].

Smart lighting technologies are advancing alongside the rise of smart homes and the demand for

automated systems that enhance comfort and security. For example, virtual assistants like Google Assistant Gemini integrate with smart lighting, enabling voice control for tasks such as adjusting lights and accessing information. Security is also improved through algorithms like FaceNet, which enable facial recognition. Users can control these systems remotely via smartphone apps, allowing for easy monitoring and alerts about potential threats, all over Wi-Fi [3].

However, as these systems become more sophisticated, they also become more complex, and this creates major problems for their design, development and testing. The complexity of optimizing these systems, especially given the large number of components and interactions, is NP-hard, meaning that traditional algorithms are often ineffective at solving these problems in a reasonable timeframe. This is where Machine Learning (ML) can play a crucial role. Using large data sets and predictive models, ML algorithms can more effectively optimize the design and performance of embedded systems. For example, ML can be used to improve system modeling, high-level synthesis, and microarchitecture design. In addition, machine learning methods can significantly reduce the time and effort required for verification and validation, which are traditionally resource-intensive tasks. Although ML has shown great promise, it is still in the early stages of application in high-level embedded system development, and further research is needed to fully realize its potential [4].

The integration of AI into smart lighting systems opens up new possibilities for improving human-centered lighting that improves the well-being of users by simulating natural light. This approach has a positive effect on circadian rhythms, alertness, mood and general health through the use of adjustable white light and advanced light control systems that regulate the color spectrum, intensity and time of exposure according to natural biological rhythms [1]. Combining AI optimization with human-centric lighting can create adaptive environments that meet individual preferences and healthcare needs.

In summary, AI-driven smart lighting systems have great potential to improve energy efficiency, comfort, and automation, but challenges like privacy, security, and technology integration must be addressed for broader adoption.

#### References

- 1) Smart Lighting Systems for Various Applications. URL: <https://www.patent-art.com/knowledge-center/smart-lighting-systems-for-various-applications/> (Date of access: 01.10.2024).
- 2) Revolutionizing Illumination: The Future of AI-Driven Smart Lighting.

URL: <https://www.directtradesupplies.co.uk/blog/revolutionizing-illumination-the-future-of-ai-driven-smart-lighting/#:~:text=AI-driven%20lighting%20systems%20can,for%20a%20serene%20bedtime%20ambiance> (Date of access: 01.10.2024).

- 3) Nguyen N., Huong P. Design and Implementation of a AI-Powered Smart home system.

URL: <https://www.researchinventy.com/papers/v13i6/M13068895.pdf> (Date of access: 01.10.2024).

- 4) Alcorta E. et al. Special Session: Machine Learning for Embedded System Design. URL: <https://www.csl.cornell.edu/~zhiruz/pdfs/ml4embedded-invited-esweek2023.pdf> (Date of access: 01.10.2024).

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## CLIMATE FORECASTING SYSTEM DISTRIBUTED ARCHITECTURE

Climate forecasting has received considerable attention due to its critical importance for decision-making in areas such as agriculture, natural resource management, and disaster preparedness. In recent years, the use of distributed architectures for Internet of Things (IoT)-based climate forecasting systems has emerged as an effective approach to provide scalable and resilient solutions. This thesis provides an overview of distributed architectures as applied to climate forecasting systems and explores how these systems can improve climate forecasting skills while overcoming key challenges of scalability, heterogeneity, and data security.

With the growing impact of climate change, there is an increasing demand for accurate climate forecasting systems. Recent advancements in distributed systems, combined with the rise of the IoT, have paved the way for advanced architectures capable of effectively predicting climatic events. IoT-based systems enable the collection of large volumes of environmental data, but they require distributed and scalable approaches to manage the heterogeneity and complexity of the data.

Distributed generation [1] is gaining attention for its role in supporting climate resilience through decentralized systems. This distributed approach aligns well with climate forecasting needs, as it enhances the

reliability of data collection across different geographical areas.

Distributed systems [2] integrated with emerging technologies like Artificial Intelligence (AI), are crucial for improving the accuracy of climate forecasting models. Such distributed architectures provide scalability, adaptability, and robustness, which are essential for addressing the growing challenges posed by climate change.

Recent research has highlighted the use of distributed architectures that incorporate both IoT devices and distributed computing paradigms such as Fog and Peer-to-Peer (P2P) networks to create effective climate forecasting systems. The article [3] proposes a hybrid and distributed architecture based on CoAP that combines fog computing with P2P overlay networks to facilitate the seamless integration of smart objects. Such systems make climate data readily available for real-time forecasting while ensuring efficient use of resources. In addition, distributed architectures [4] address key issues related to heterogeneity, scalability, and interoperability using a multi-tiered model. This model provides different levels of abstraction, simplifying data management and integration of new IoT devices.

Integrating AI models with traditional forecasting systems is another way to improve climate forecasts. Hybrid methods of hydroclimatic forecasting combine data-driven AI models with physical models to achieve more accurate predictions of climate events [5]. This integration allows for improved forecasting skills by taking advantage of machine learning, which can cope with the inherent errors of numerical models and learn efficiently from large data sets. In addition, the combination of AI and climate models allows forecasts to be made over a wide range of time scales, from short-term weather forecasts to long-term climate forecasts.

The introduction of distributed IoT systems raises several security concerns due to their large-scale deployment and potential vulnerability to cyberattacks. The article [6] addresses this problem by proposing a blockchain-based architecture that provides a secure and scalable IoT network. Blockchain combined with AI improves the reliability of climate forecasting systems by adding layers of data integrity and security, which is crucial given the sensitivity of the data being processed. Anomaly detection based on machine learning at the gateway level further protects against malicious activity, providing a solid foundation for a secure climate forecasting system.

The development of distributed climate forecasting systems involves a few challenges, such as the integration of diverse data sources, the need for secure communication protocols, and the high computational requirements for processing complex models. However, the opportunities are significant. By using a distributed architecture, the system can achieve high scalability and