SCIENCE EDUCATION AND COMPUTATIONAL THINKING: INTERACTIVE LEARNING WITH ARTIFICIAL INTELLIGENCE

Uğur SARI
Kırıkkale University
E-mail: ugursari@kku.edu.tr
ORCID: 0000-0002-3469-8959

Hüseyin Miraç PEKTAŞ
Kırıkkale University
E-mail: miracpektas@kku.edu.tr
ORCID: 0000-0001-5963-5877

INTRODUCTION

The rapidly transforming knowledge and technology ecosystem of the twenty-first century has shifted the focus of science education from mere transmission of concepts to the holistic development of twenty-first-century skills such as critical thinking, creative problem-solving, collaboration, communication, digital literacy, and data literacy. In this context, science education aims to cultivate learners who are not passive recipients explaining natural phenomena, but active participants who collect and analyze data, construct models, and generate solutions through computational tools. Learning experiences designed around interdisciplinary connections and real-world problems integrate inquiry-based learning processes, modeling and simulation, evidence-based reasoning, and ethical awareness, thereby making science learning meaningful and enduring.

Computational Thinking (CT) and Artificial Intelligence (AI) are among the key driving forces of this transformation in science education. CT represents a contemporary way of thinking that encompasses systematic problem solving, decomposition into subproblems, abstraction, the development of algorithmic solutions, modeling/simulation, and the iterative cycle of testing, debugging, and generalization (Juškevičienė et al., 2021; Tsarava et al., 2022). Within the science context, CT makes relationships between variables visible, integrates the triad of experiment–data–model, and enables students to deepen their scientific reasoning through quantitative and computational tools. AI, in turn, supports this process through personalized feedback, learning analytics, pattern recognition, and adaptive simulations or virtual laboratories, thereby enhancing the visualization of abstract concepts, data-driven decision-making, and higher-order thinking skills (García et al., 2019). Consequently, the synergy of CT and AI can create an interactive, evidence-based, and productive learning ecosystem within science classrooms.

The purpose of this chapter is to examine the interaction between CT and AI in science education from both theoretical and practical perspectives. The chapter first defines CT and its core components, followed by an exploration of how this mode of thinking can be integrated into science education through inquiry-based learning environments. Subsequently, the conceptual connection between CT and AI is discussed, highlighting how the algorithm–data–model cycle intersects with the perception, learning, and representation dimensions of AI. The following section focuses on AI-supported interactive learning applications, examining intelligent tutoring systems, data analysis through machine learning, adaptive simulations, virtual laboratories, and feedback mechanisms based on learning analytics through illustrative activities. The chapter concludes with implications for teachers and researchers, including applicable instructional principles, assessment and evaluation approaches, and ethical considerations.

Computational Thinking: Definition and Components

Computational thinking (CT) is an approach to thinking that enables individuals to solve complex problems systematically, creatively, and algorithmically (Sarı et al., 2025). The concept was first introduced by Papert (1980) to explain the cognitive effects of computer use in education, but it gained widespread recognition through Wing's (2006) definition. According to Wing (2006), CT is "*the thought process involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent*." This definition positions CT not merely as a programming skill but as a universal mode of thought that every individual can use to solve problems encountered in everyday life.

Barr, Harrison, and Conery (2011) define CT as a multifaceted cognitive framework encompassing processes such as data collection and analysis, algorithm development, automation, solution generation, and generalization. Grover and Pea (2013) emphasize that at the core of this approach lie abstraction, decomposition, algorithmic thinking, debugging, and generalization. Similarly, Kalelioğlu et al. (2016) relate CT to the problem-solving process, describing it as involving the sequential steps of problem redefinition, solution planning, testing, and generalization of results. In this sense, CT can be viewed not only as a product of computer science but also as a digital-age adaptation of fundamental cognitive processes. To solve a problem, an individual first decomposes the complex structure into smaller parts (decomposition), selects relevant information (abstraction), transforms the solution into a series of logical steps (algorithmic thinking), tests outcomes, and applies them to new situations (generalization). Each of these processes constitutes a systematic cognitive problem-solving cycle. Although different classifications exist in the literature, most researchers share similar perspectives regarding the core components of CT (Barr & Stephenson, 2011; Grover & Pea, 2013; Kalelioğlu et al., 2016; Weintrop et al., 2016). These components can be summarized as follows:

- ***Decomposition:*** The ability to break down complex problems into smaller, manageable subproblems.

- ***Pattern Recognition:*** The skill of identifying similarities and differences in data to make generalizations.
- ***Abstraction:*** The process of selecting the essential information relevant to the problem while eliminating unnecessary details.
- ***Modeling and Simulation:*** The capability to construct and test representative models of real-world systems.
- ***Algorithmic Thinking:*** The ability to develop logical, step-by-step procedures to solve problems.
- ***Data Handling:*** The process of collecting, organizing, analyzing, and interpreting relevant data.
- ***Automation:*** The ability to perform repetitive processes using computer-assisted tools.
- ***Parallelism:*** The cognitive awareness that allows for the simultaneous management of multiple processes.
- ***Debugging:*** The process of verifying the correctness of solutions, identifying errors, and correcting them.
- ***Generalization:*** The ability to apply developed solutions to similar problems.

Taken together, these components demonstrate that CT is not merely a computational process but also one of the fundamental pillars of analytical thinking, systematic inquiry, and problem-solving ability. As individuals acquire these processes, they become more efficient problem solvers, better interpreters of data, and more capable of generating transferable knowledge across contexts.

CT is not limited to cognitive processes alone; it also encompasses affective dimensions such as self-confidence, patience, curiosity, collaboration, and perseverance (Barr & Stephenson, 2011). Especially when dealing with open-ended and ill-defined problems, learners' willingness to experiment, learn from mistakes, and develop strategies throughout the process are crucial factors supporting the development of CT. In this respect, CT strengthens both learners' cognitive flexibility and learning autonomy (Shute, Sun, & Asbell-Clarke, 2017).

In summary, CT is an interdisciplinary mode of thought that integrates cognitive, algorithmic, and creative dimensions of problem solving. This framework extends beyond programming skills to include thinking with data, developing systematic strategies, and producing adaptable solutions for new situations. The next section explores the relationship between this mode of thinking and science education, focusing on how CT skills can be developed in students and integrated into science learning processes.

Computational Thinking and Science Education

CT, as a mode of thought that supports interdisciplinary problem-solving processes beyond the scope of computer science, has gained increasing importance in science education. The primary goal of science education is to enable students to make sense of natural phenomena, develop and test hypotheses, and derive meaningful conclusions from scientific data. Throughout this process, students are expected to employ skills such as inquiry-based reasoning, data analysis, modeling, and evidence-based argumentation. CT provides a cognitive framework that aligns closely with these skills (Weintrop et al., 2016; Sarı & Karaşahin, 2020).

Science problems are often open-ended, involve multiple variables, and require experimental approaches. CT enables students to understand complex systems, develop solutions by decomposing problems into subcomponents, and adopt systematic habits of mind (Grover & Pea, 2013; Malik et al., 2018). During experimental inquiry, students define the problem, identify variables, collect and analyze data, and then generalize the findings. This process directly corresponds to the computational cycle of decomposition, abstraction, algorithmic thinking, modeling, testing, and generalization (Sarı et al., 2025). Therefore, CT can be integrated into both the cognitive and methodological structures of science teaching.

Science learning environments, by their nature, are well suited for computational processes. Experiments, measurements, and observations are based on specific algorithms; data are systematically collected and analyzed. For instance, when designing an experiment, students follow steps such as determining measurement intervals, adjusting repetition frequencies, and interpreting data sets. These steps are cognitively equivalent to algorithmic operations (Sarı et al., 2025). Additionally, identifying and correcting errors during experimentation parallels the “debugging” process in computation. This approach not only helps students reach accurate results but also allows them to evaluate and refine their problem-solving processes.

Modeling and abstraction processes in science teaching also correspond closely with the key components of CT. When students attempt to explain a physical phenomenon, they simplify the model, eliminate unnecessary variables, and construct an abstract representation of the system. This directly mirrors the concept of abstraction in CT (Sarı & Karaşahin, 2020; Zakwandi & Istiyono, 2023). Similarly, the generalization and testing of experimental outcomes under different conditions align with the process of generalization. In this way, students simultaneously engage in both scientific and computational reasoning.

The effective use of CT in science education has become increasingly feasible with the proliferation of technology-enhanced learning environments. Microcontroller-based systems (e.g., Arduino), sensors, and data acquisition software directly enhance students’ data processing and analysis skills (Sarı, 2019; Papadimitropoulos, Dalacosta, & Pavlatou, 2021). Using these tools, students collect experimental data, create graphs in digital environments, and interpret results algorithmically. Through this process, they experientially learn both automation and data analysis skills. Moreover, simulations and virtual laboratories allow students to visualize complex systems and explore the effects of parameter changes. Such digital tools concretize abstract concepts and enable students to test their own models and hypotheses (Sarı et al., 2020). Hence, technology-supported science activities transfer CT components directly into practice, reinforcing students' higher-order thinking skills (Sarı et al., 2025).

STEM education integrates science, technology, engineering, and mathematics disciplines to foster problem-solving and innovative thinking skills in students (Sarı et al, 2022). CT serves as the cognitive engine of this integrative framework. There are clear parallels between the engineering design process and the CT process—both involve defining the problem, conducting research, developing solutions, creating prototypes, testing, and improving them (Sarı & Karaşahin, 2020). In these processes, students employ both scientific and computational reasoning to produce innovative solutions. Moreover, CT and STEM share a common foundation for fostering twenty-first-century skills. Creativity, critical thinking, collaboration, communication, and algorithmic reasoning lie at the core of both CT and STEM (Korkmaz, Çakır, & Özden, 2017). In this sense, science classrooms evolve into dynamic learning environments where students not only acquire scientific knowledge but also apply these skills to real-world problems.

In conclusion, the integration of CT into science education deepens students' scientific process skills while supporting the development of higher-order abilities such as cognitive flexibility, self-regulation, and learning motivation. CT-based science activities promote systematic thinking in processes such as data collection, modeling, testing, and generalization, thereby enhancing students' active engagement in the learning process.

Computational Thinking and Artificial Intelligence

Computational thinking (CT), as a cognitive framework that integrates computational power into problem-solving processes, shares a strong conceptual relationship with artificial intelligence (AI). Through skills such as algorithmic thinking, data analysis, modeling, and abstraction, CT systematizes the human mode of reasoning, while AI transfers these cognitive processes into the digital domain, enabling machines to learn (Wing, 2008; Floridi, 2019). Therefore, integrating AI into computational thinking frameworks is crucial for understanding the intersection of human and machine cognition in problem-solving contexts.

In an AI-based learning ecosystem, the scope of CT extends beyond algorithm design to include more complex cognitive processes such as data classification, prediction, modeling, and evaluation. Brummelen et al. (2019) and García et al. (2019) identify five core computational concepts associated with AI: classification, prediction, generation, training/validation/testing, and evaluation. These stages closely parallel the cyclical structure of CT—data collection and processing, algorithm construction, model formation, testing, and generalization. In this way, AI transforms CT from merely a way of thinking into an applied field at the level of “learning systems.”

Machine learning, as a core component of AI, allows computers to emulate human learning processes and improve their performance over time (Essinger & Rosen, 2011). While CT systematizes human problem-solving processes, machine learning translates these processes into digital environments (Heintz, 2022). Thus, both concepts play complementary roles in problem solving. Through machine learning applications, students develop computational skills such as data analysis, pattern recognition, prediction, and model construction (García et al., 2019; Dohn et al., 2022). Consequently, AI-supported learning activities not only foster technical knowledge but also stimulate higher-order cognitive abilities such as analytical thinking, creativity, and critical decision-making.

The integration of AI into education expands students’ cognitive awareness while deepening their understanding of ethical, social, and philosophical dimensions. Gadanidis (2017) and Gadanidis et al. (2024) emphasize that AI is not merely a technology but a learning environment that transforms how students think. In this context, students move beyond understanding how AI systems function to questioning their outcomes, recognizing biases, and evaluating the societal implications of algorithmic decision-making. Thus, when considered together, CT and AI provide a holistic learning approach encompassing both cognitive and ethical dimensions.

AI literacy has gained increasing significance within contemporary educational systems. Incorporating AI-related content into K–12 curricula is essential for helping students grasp fundamental concepts of artificial intelligence. In studies conducted by Ho and Scadding (2019), two AI activities at the elementary level exemplify this approach. In the first activity, students learned about data labeling and feature extraction through a card-matching task that mimicked facial recognition. In the second activity, they engaged with machine learning principles using Lego Mindstorms EV3 robots, constructing their own “learning systems” through cycles of prediction, trial and error, and feedback. Such activities bridge abstract AI concepts with tangible science learning experiences.

The K–12 initiative and the AI4K12 standards link AI literacy to computational thinking skills and define five core themes: perception, representation and reasoning, learning (machine and deep learning), natural interaction, and societal impact (Touretzky et al., 2019). These themes aim to help students understand the cognitive functioning of AI while developing a human-centered perspective. Choi (2019) and Min and Shim (2021) highlight that the assessment of AI-related competencies remains an emerging area, whereas Kim and Lee (2020) developed tools for measuring students’ attitudes toward and literacy in AI. These findings indicate the need for educational systems to restructure their AI assessment criteria.

In recent years, AI has also demonstrated a transformative impact in the context of teacher education and learning design. Annuš (2024), Foster (2024), and Ajlouni et al. (2023) have shown that AI technologies contribute significantly to improving lesson planning, developing instructional materials, and personalizing learning processes. Likewise, Ali et al. (2019) and Wong (2020) emphasize that teachers and school systems must pedagogically integrate AI's potential through innovative approaches. In this regard, AI functions not merely as a tool but as a cognitive partner that enables the redesign of learning processes.

In conclusion, the integration of computational thinking and artificial intelligence enhances not only students' problem-solving abilities but also their critical awareness, ethical reasoning, and social responsibility. This integration demonstrates that AI-supported computational thinking in science education has evolved into a learning paradigm that is both cognitively and value-oriented.

Artificial Intelligence–Supported Interactive Learning in Science Education

In recent years, the convergence of increased computational capacity, large data sets, and advanced machine learning algorithms has paved the way for remarkable progress in artificial intelligence (AI) technologies. As a subfield of computer science, AI encompasses the design of systems capable of performing cognitive processes traditionally associated with human intelligence, such as learning, reasoning, adaptation, and self-correction (Dobrev, 2012). This development necessitates the integration of knowledge and skills related to AI into educational processes to prepare individuals to participate effectively in an AI-driven world (Eaton et al., 2018).

The integration of AI into education is not confined to higher education; it is increasingly recommended that foundational concepts be introduced at early ages to help students understand these technologies (Heintz, 2021). AI-supported teaching and learning applications have rapidly expanded across disciplines such as language education (Pokrivcakova, 2019), mathematics (Gadanidis, 2017), biology (Perrakis & Sixma, 2021), and physics (Cheah, 2021). These systems provide personalized and interactive learning environments through intelligent tutoring assistants (Kim et al., 2020) and learning agents (Petersen et al., 2021) that adapt content to learners' profiles. Large language models such as ChatGPT demonstrate transformative potential in education by offering dynamic, inquiry-driven, and feedback-based learning experiences (Baidoo-Anu & Owusu Ansah, 2023).

Machine learning, one of the most influential components of AI in science education, personalizes learning experiences according to individual differences and transforms learning into an interactive process (Alam, 2022). The integration of computational processes such as data analysis, model construction, and hypothesis testing with AI in science teaching enhances students' scientific and algorithmic reasoning skills. Indeed, studies conducted at the university level have shown that AI has been used to identify misconceptions related to topics such as the greenhouse effect and electricity (Kökver et al., 2024; Pektaş et al., 2025), and that automatic AI modules have been developed to analyze preservice teachers' learning styles (Pektaş, 2025). However, systematic investigations of AI applications in science education, particularly at the primary and secondary levels, remain limited (Akgun & Greenhow, 2021; Xu & Ouyang, 2022). The use of AI in science teaching is often examined within the contexts of STEM or e-learning, while holistic approaches from a general science education perspective are still emerging (Tang et al., 2023). This highlights the need for comprehensive studies that reveal the potential of AI-supported interactive learning environments in science education.

AI-based learning environments support both students' scientific process skills and higher-order cognitive competencies. Children, often unconsciously, interact with AI-based applications in their daily lives, such as facial recognition or voice assistant technologies. Therefore, understanding how AI systems function enables them to interpret the digital world they inhabit more consciously. Developing AI awareness at an early age is not only a technological skill but also a crucial step in fostering critical thinking, ethical reasoning, and social responsibility.

Kandlhofer and Steinbauer (2021) and Su and Zhong (2022) emphasize that introducing AI education at an early age strengthens students' abilities to understand and create technology. Furthermore, integrating AI into science classes increases students' interest in science, encourages them toward innovative applications, and contributes to cultivating future AI experts (Ali et al., 2019; Heintz, 2021). In this respect, AI is not merely a tool in science education but an interactive learning partner that deepens students' computational thinking processes.

A Sample Activity Integrating Computational Thinking and Artificial Intelligence in Science Education

This section presents an example of an AI-supported learning activity that integrates computational thinking (CT) skills into science education. In this activity, students are tasked with developing an intelligent tutoring system based on machine learning. The system analyzes onion epidermis cell images obtained through a microscope and provides feedback to students on visual quality and accuracy using learning analytics. Through this process, students have the opportunity to experience AI's mechanisms of data processing, classification, and feedback generation within a science laboratory context. The activity is structured around the core stages of computational thinking—abstraction, decomposition, modeling, algorithm design, testing and debugging, automation, and generalization. The stages of the activity and the operations performed are described below.

Activity Title: If Only I Could Automatically Find the Cell

Abstraction

In this phase, students focused on the essence of the problem by moving away from complex data and identifying the main objective: *"When an image is displayed, the system should be able to recognize whether it is an onion epidermis* *and assess its clarity to provide feedback."* Students captured onion epidermis images using a microscope and also collected additional microscopic onion epidermis images from the internet for comparison. They recorded colored images using staining chemicals such as Lugol's solution (see **Figure 1**) and methylene blue (see **Figure 2**) and as additional data. The image without onion epidermis is shown in **Figure 3**. During this process, a dataset of 535 onion epidermis images was created.

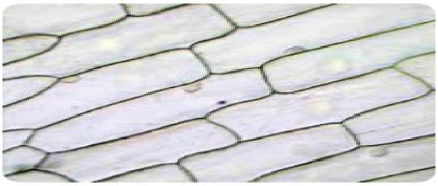


Figure 1. *Clear Image*

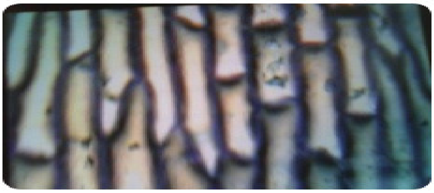


Figure 2. *Blurred Image*

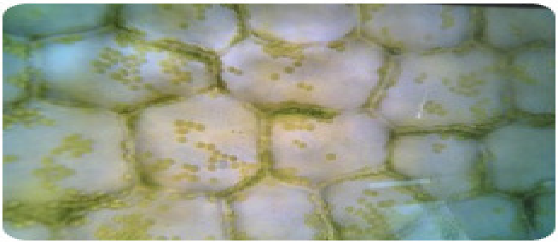
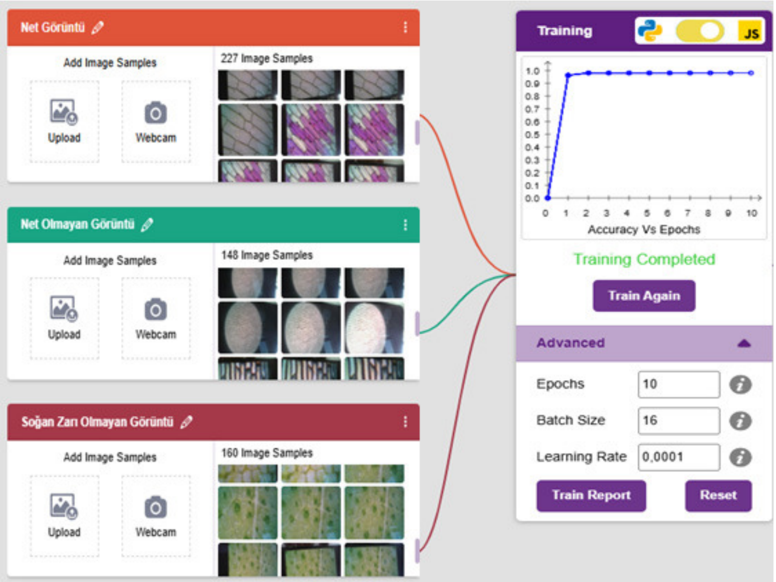


Figure 3. *Image Not Showing Onion Epidermis*

Decomposition

In this stage, students decomposed the image data and performed a classification process. They categorized the images into three distinct groups: non–onion epidermis images, blurred images, and clear images. As a result of this process, the dataset was divided into 148 blurred images, 160 non–onion epidermis images, and 227 clear images. (see **Figure 4**).



Epochs 10

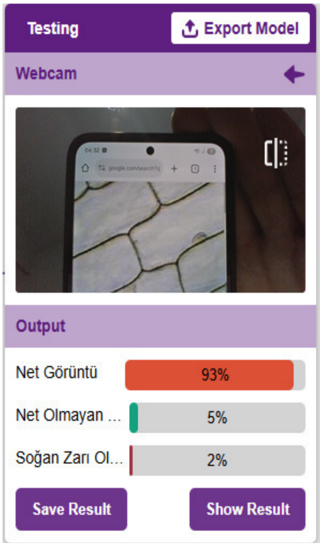
Batch Size 16

Learning Rate 0,0001

Figure 4. *Image Classification and Model Training Process*

Modeling

In this stage, students divided the problem situation into subproblems and identified the variables for each. The first subproblem concerned the classification of images, while the second focused on the feedback generated by the learning analytics system. Using an artificial intelligence tool, the students trained the system with the collected data and prepared it for implementation. In this model, the value **0** represented images that were *not onion epidermis*, **1** indicated *blurred images*, and **2** denoted *clear images*. (see **Figure 5**).



Net Görüntü 93%

Net Olmayan ... 5%

Soğan Zarı Ol... 2%

Figure 5. *Developed Artificial Intelligence Model*

Algorithm Design

After completing the training of the dataset, students were required to test the results by capturing an image of the onion epidermis through the microscope and uploading it to the instructional material via a mobile phone. If the image was clear, it would be classified under category **2**; if it was not clear, under category **1**; and if it was not an onion epidermis image, under category **0**, with corresponding accuracy rates displayed. As a result, an AI-supported instructional material was designed to enable students to test the accuracy of their microscopic images of the onion epidermis with high precision. Therefore, in this stage, students were required to develop an algorithm. The designed algorithm is presented below:

- When the **space key** is pressed, open the image recognition window.
- Start the **video stream**.
- If the image is clear, display the message: *"Congratulations!"*
- If the image is blurred, display the message: *"The image is not clear; please recheck the specimen!"*
- If the image is not an onion epidermis, display the message: *"This is not an onion epidermis image!"*

At this stage, students used algorithmic thinking and conditional statements (*if–else*) to understand how AI systems make decisions.

Testing and Debugging

Working collaboratively, students made real-time improvements to enhance image quality. To ensure the AI model functioned efficiently, they created additional and more diverse image datasets. Consequently, the developed AI model was continuously tested with new images, minimizing potential errors through iterative refinements. Through this process, students directly experienced the "learning" nature of machine learning via testing and debugging cycles.

Automation

After writing the algorithm, students realized that they needed to include a plugin enabling continuous repetition. A *"repeat forever"* command was added to keep the system running constantly, allowing the model to automatically generate new feedback when encountering different images. Through this step, students gained an understanding of the importance of automation and cyclic execution within an algorithmic process (see **Figure 6**).

```
boşluk ▾ tuşuna basılınca
open recognition window
turn on ▾ video on stage with 0 transparency
sürekli tekrarla
  eğer is identified class - Net ▾ Görüntü ? ise
    Tebrikler! de
  eğer is identified class - Net Olmayan ▾ Görüntü ? ise
    Görüntü net değil, preparatı tekrar kontrol ediniz! de
  eğer is identified class - Soğan Zarı Olmayan ▾ Görüntü ? ise
    Görüntü soğan zarı görüntüsü değil! de
```

Figure 6. *Development of the Continuously Repeating Artificial Intelligence Module*

Students read the feedback displayed by the learning analytics system and repeatedly followed the given steps to obtain a clear and accurate image.

Data Collection, Representation, and Analysis

Students examined whether the developed artificial intelligence (AI) model functioned correctly and collected data to make inferences. First, they gathered data related to the model's accuracy rates (*see* **Figure 7**). By evaluating the learning analytics results, students identified in which categories the system performed more successfully and represented their findings using graphical visualizations. The data related to other artificial intelligence computations are presented in **Figure 8**. **Figure 9** presents the data obtained from learning analytics.

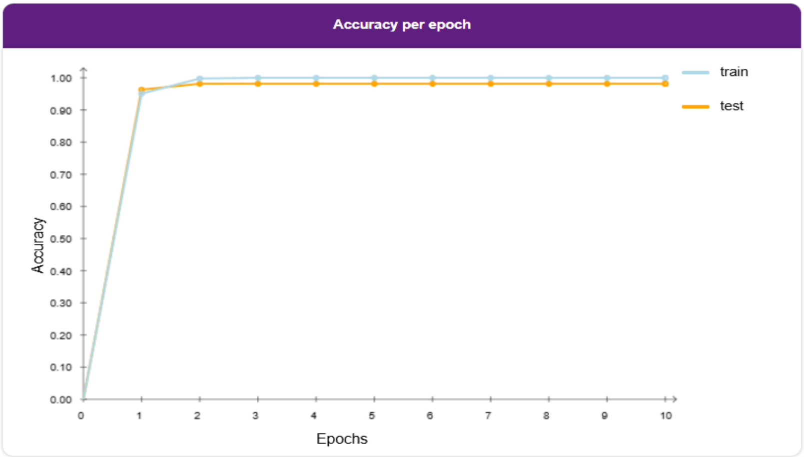
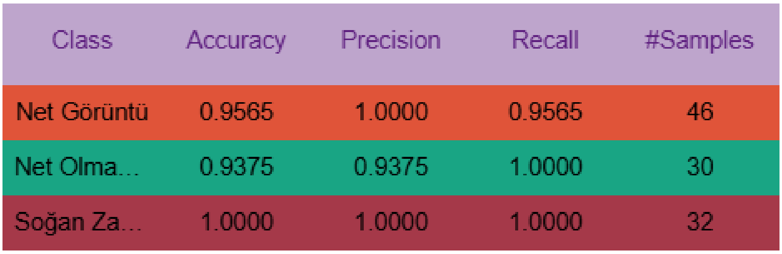


Figure 7. *Data Related to Accuracy Rates*



Class	Accuracy	Precision	Recall	#Samples
Net Görüntü	0.9565	1.0000	0.9565	46
Net Olma...	0.9375	0.9375	1.0000	30
Soğan Za...	1.0000	1.0000	1.0000	32

Figure 8. *Class, Accuracy, Precision, and Recall*

Figure 9. *Data Related to Learning Analytics*

Generalization

At the end of the activity, students realized that the AI model they developed was not limited to microscopic images but could also be applied to other science topics—such as cell division and plant tissue identification. In this way, the generalization component of computational thinking was concretized within an interdisciplinary context.

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ABOUT THE AUTHORS

Uğur SARI has been serving as a Professor at the Department of Mathematics and Science Education, Kırıkkale University, since 2014. He teaches undergraduate and graduate courses in physics and physics education. He holds M.Sc. and Ph.D. degrees in Physics. His research interests include computer programming, computational thinking, artificial intelligence, STEM education, and technology-enhanced physics instruction. His scholarly work primarily focuses on the integration of 21st-century skills into science education, pedagogical models of computational thinking, and the design of digital learning environments.

Hüseyin Miraç PEKTAŞ is a Research Assistant at the Department of Mathematics and Science Education, Faculty of Education, Kırıkkale University, located in the city of Kırıkkale, Turkey. He holds a Ph.D. in Mathematics and Science Education from Amasya University. In 2025, he completed his thesis titled “Design of an Artificial Intelligence-Supported Student Recognition System and Its Effect on the Conceptual Change Process in Differentiated Instruction.” His main areas of interest are science education, STEAM, artificial intelligence, robotic coding, data mining, and augmented reality applications. He founded a company called “Code Kids Academy” within the Kırıkkale University Technopark, where he teaches coding and STEAM applications to elementary and middle school students. He has also served as a researcher and consultant on many TÜBİTAK-supported projects.

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