A TPACK-Aligned Teaching Approach: Image Recognition via Convolutional Neural Networks for Artificial Intelligence Education in Teacher Training

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Abstract: Convolutional Neural Networks (CNNs) are the technology behind many familiar applications such as facial recognition, autonomous driving, medical imaging, and augmented reality. This paper introduces a practice-based approach designed to help ICT and digital education educators teach CNNs effectively by combining both theoretical concepts and hands-on activities. Leveraging established educational frameworks like TPACK for teacher competencies and Bloom's Taxonomy for learning goals on different cognitive levels to ensure all important aspects about CNNs are covered. Our approach includes engaging demonstrations, practical programming exercises, and critical discussions on real-world applications and issues such as transparency, explainability, and data quality in Neural Network training.

Introduction

Autonomous driving, technologically assisted medical imaging diagnostics, facial recognition and self-service supermarkets are just some examples of image recognition applications that made significant technological advances in recent years (Li et al., 2022) largely benefiting from modern developments in machine learning, a data-driven approach in artificial intelligence. The process of image recognition in machine learning usually relies on Convolutional Neural Networks (CNNs), a combination of mathematical operations that extract features from large volumes of training data in a sub-symbolic manner to classify image contents. (Russell & Norvig, 2021) CNNs can be trained to visually distinguish images of cats and dogs, identify road signs or recognize unique facial features - without requiring the painstaking task of providing explicit instructions on which visual features are relevant for classification. While the advantages of using CNNs for image recognition are undeniably significant, a major drawback is their sub-symbolic 'black box' nature. This results in a lack of transparency and interpretability - an issue that is particularly problematic in sensitive fields such as medical diagnostics or criminal justice, where misclassifications can have severe real-world consequences and thus require explainability. Further potential issues include dependency on the quality and representativeness of training data, overfitting and underfitting, vulnerability to data poisoning and adversarial attacks (Li et al., 2022), high computational and energy costs, difficulties in handling variations (such as rotations, scale variations, occlusions, or deformations) (Mumuni & Mumuni, 2021), and the need for large, accurately labeled datasets. Recognizing and understanding the root of these challenges is essential for accurately assessing the risks and opportunities associated with machine learning approaches - a crucial competency for educators. This paper outlines a proposal for a teaching approach that equips ICT and digital education educators with the conceptual, theoretical, pedagogical, and practical competencies required to design and deliver comprehensive AI courses focused on CNNs. To develop a training program that addresses all important aspects and educational goals, the TPACK competency framework and Bloom's Taxonomy will be used as proven and tested guidelines for the proposed approach. Image recognition using CNNs is particularly well-suited as a teaching topic due to its inherent visual nature, which allows for the clear illustration of intermediate computational steps, such as the convolution and pooling operations. These visually demonstrable processes make abstract mathematical concepts more tangible, thereby enhancing comprehension. Moreover, the challenges and limitations encountered in CNNs - such as sensitivity to input data variations, overfitting and underfitting, and the 'black box' problem - reflect broader issues in Neural Network-based machine learning. The diverse real-life applications of CNNs further underscore the topic's relevance by building on students' everyday experiences and sparking engagement, while also encouraging them to think critically about the real-world benefits and risks of AI technologies.

Teaching approach

Although several comprehensive collections of educational applications and resources for AI and machine learning in the K-12 age group exist—such as ENARIS (ENARIS, 2021a; Kandlhofer et al., 2023) , AI4K12 (AI4K12 Initiative, 2021), Elements of AI (University of Helsinki, 2018), DAIly curriculum (AI Education Initiative at MIT, 2023), Machine Learning for Kids (Lane, 2017), AI unplugged (Lindner & Seegerer, 2020), Teachable Machine (Google LLC, 2017), AI Literacy Day (InnovateEDU Inc., 2024), and the collection of AI teaching resources by the Dresden University of Technology's Chair of Didactics of Computer Science - there is comparatively little material on teaching approaches for training educators in AI-related topics (e.g. EDLRIS (Kandlhofer et al., 2021)). While these K-12 teaching resources form an essential component of educators' expertise, additional elements are required to fully equip teachers to deliver comprehensive AI lessons.

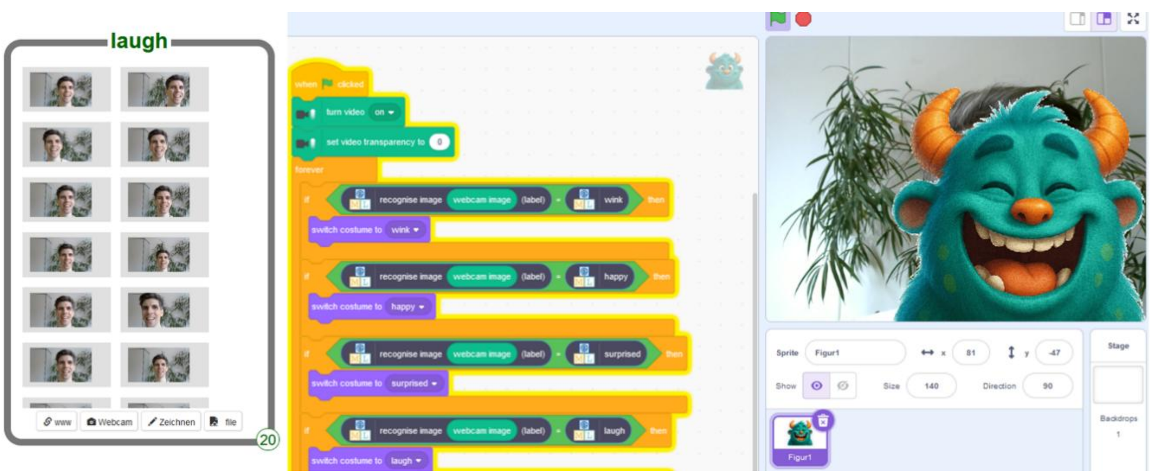

Figure 1: Motivational introductory application to the world of CNNs: Training data, code and live view of a teaching example for an augmented reality face mask. A CNN is trained on MachineLearningForKids.co.uk to detect facial expressions using previously recorded training data. Afterwards the same CNN is embedded in Scratch to classify facial expressions from a live webcam input and a face mask is pinned to the face accordingly. The mask artworks have been created using DALL-E 3.

Building primarily on a review and selection of relevant materials and methodologies, this practice-based paper presents a proposal for teaching the functionalities and purposes of Convolutional Neural Networks (CNNs) to educators. By integrating the TPACK framework and Bloom's Taxonomy, the approach ensures that educators develop multifaceted competencies and gain an adequate understanding of CNNs at all key levels. Our lessons are basically structured as follows:

- Motivation and Introduction: Discussion of current real-life applications of CNNs like autonomous driving, medical imaging diagnostics, facial recognition and augmented reality.

- Motivation: Train a Neural Network (NN) on MachineLearningForKids.co.uk (Lane, 2017) to classify facial expressions or hand gestures used in "rock, paper, scissors" via webcam input. Subsequently, the trained Neural Network is integrated into a Scratch program (Massachusetts Institute of Technology, 2006) either to play rock–paper–scissors against an algorithm or to overlay virtual comic-style facial masks that adapt to the user's facial expression (Figure 1).
- Introduction to Neural Networks, perceptrons, weighted connections and activation functions.
    - Unplugged activity: "Brain in a bag" (McOwan & Curzon, 2014).
    - Modeling a logical "OR" using a single perceptron as pen and paper activity, using the xNN Open Roberta Lab (Fraunhofer-Institut AIAS, 2014) or Python.
    - Modeling a logical "XOR" or problems of similar complexity using a small multi-layer Neural Network and outlining the concept of deep learning.
    - Programming a simple Neural Network to classify iris species using the iris flower dataset and discussing linear separation tasks (Schwaiger & Steinwender, 2020).
- Introduction to image computation based on pixels and values.
- Discussion of input and output layer dimensions of a Neural Network for image classification tasks.
- Discussion of the structure of a fully connected deep Neural Network that could be used for image classification without the use of convolution and associated limitations.
    - Programming a Neural Network in Python to classify written digits using the MNIST dataset.
- Introducing convolution filters for line detection (ENARIS, 2021b) and gaussian blurring.
- Introducing pooling layers using different pooling approaches for downsampling images while maintaining limited relative spatial information (Frese & Lorenz, 2024; Russell & Norvig, 2021).
- Explain the structure of Convolutional Neural Networks (CNNs) (Frese & Lorenz, 2024; Li et al., 2022; Russell & Norvig, 2021)building upon the gathered information (Figure 2).
- Activity: Try out Google quickdraw as an example on how large volumes of labeled datasets can be gathered (Google LLC, 2016).
- Activity: AI unplugged "The Good-Monkey-Bad-Monkey Game" (Lindner et al., 2019; Lindner & Seegerer, 2020).
- Discussion of the risks of classification errors depending on the quality and representativeness of training data, over- and underfitting, vulnerability to adversarial attacks, difficulties in handling variations like rotations, scale variations, occlusions or deformation and the requirement of large datasets that have been correctly labeled.
- Activity: Recreate the Scratch program from the introductory example with the facial expression dependent augmented comic monster mask or create a different program that incorporates image classification through machine learning.
- Discussion of similarities and differences in the ways that CNN and humans classify unknown images and possible impacts.
- Activity: Highlight image areas that are most important for the decided tag during classification using the GenAI teachable machine (Pope, 2023) or the "Explainable AI" worksheet on Machine Learning for Kids.
- Discussion of real-life implications of misclassifications, certainty and robustness of decisions based on Neural Network outputs including the context of explainable AI.
- Activity: Create a CNN in python to classify images from the CIFAR-10 dataset (Krizhevsky et al., 2009).
- Discussion of common students' conceptions (K. Kim et al., 2023; Lindner et al., 2021) about AI and subject didactic approaches to this topic.

TPACK and Bloom's Taxonomy

TPACK (S. Kim et al., 2020; Mishra et al., 2023) and Bloom's Taxonomy (Krathwohl, 2002) serve as foundational frameworks in this proposal by addressing two complementary dimensions of educator preparation. On one hand, the TPACK framework integrates technological, pedagogical, and content knowledge, providing a comprehensive model that reflects the complex skill sets teachers require to effectively incorporate CNNs and related AI technologies into their lessons. This multidimensional approach ensures that educators are equipped not only with subject-specific insights but also with the practical strategies necessary for engaging and innovative instruction. On the other hand, Bloom's Taxonomy offers a structured means of classifying and targeting the levels of cognitive understanding—from basic knowledge acquisition to higher-order thinking skills such as analysis and creation. Together, these frameworks ensure that teacher training is both broadly competent and focused on creating an understanding of CNN functionalities in a manner that is adaptable and pedagogically robust. Tables 1 and 2 show how our course structure can be mapped into the TPACK framework domain and onto Bloom's Taxonomy.

TPACK Domain	**Competencies**
TK (Technological Knowledge)	Use of Python, Open Roberta Lab, Scratch, Machine Learning for Kids, GenAI Teachable Machine
PK (Pedagogical Knowledge)	Motivation and real-life CNN examples, unplugged activities ("Brain in a Bag", "Good Monkey–Bad Monkey"), Google Quickdraw
CK (Content Knowledge)	Introduction to Neural Networks and perceptrons, CNN structure, convolution filters (e.g., line detection, Gaussian blur), pooling, pixel/image computing, input/output layer dimensions, classification risks and limitations, CNN vs. human classification, explainable AI
TPK (Technological Pedagogical Knowledge)	Use of tools such as the GenAI Teachable Machine or the “Explainable AI” worksheet to highlight critical image regions
TCK (Technological Content Knowledge)	Technical limitations of non-convolutional NNs, CNN architecture (layer structure, dimensional constraints), dataset requirements and labeling, adversarial attack vulnerability
PCK (Pedagogical Content Knowledge)	Addressing implications of misclassifications, robustness of AI decisions, handling common student misconceptions about AI and didactic strategies
TPACK (Technical Pedagogical Content Knowledge)	Development of custom programs (e.g., a Scratch project incorporating webcam input for augmented reality masks or rock–paper–scissors)

Table 1: Teacher competencies mapped to TPACK framework domains.

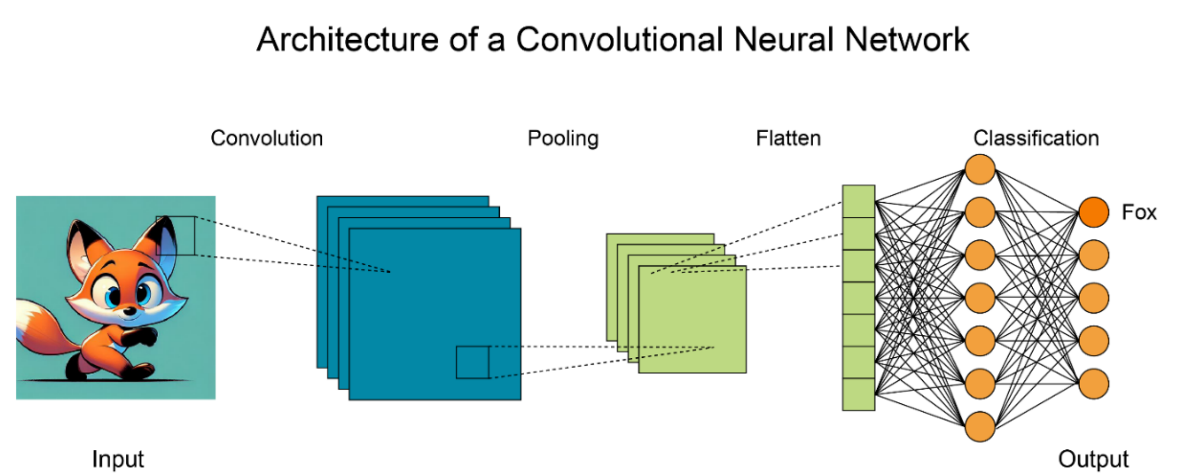

Figure 2: Architecture of a Convolutional Neural Network. The Input image is split into its RGB channels, convolved using filters to generate feature maps and pooled to reduce the dimension while preserving relative spatial information. This process of convoluting and pooling is repeated several times. Finally, the feature maps are flattened into a one-dimensional array and classified through a fully connected pre-trained Neural Network, whose final layer outputs the classification result. The input image (fox) was generated using DALL-E 3.

Bloom's Level	Teaching Examples
Remember	Real-life CNN examples (e.g., autonomous driving), image computing basics, convolution filters, pooling layers, training data and Quickdraw
Understand	Introduction to Neural Networks, perceptrons, weights, and activation functions (pen & paper or unplugged), CNN structure explanation, Unplugged "brain in a bag", Good/Bad Monkey Game
Apply	Train NN on Machine Learning for Kids for rock–paper–scissors, Modeling OR/XOR, iris dataset classification; Train CNN in python to classify images from the CIFAR-10 dataset
Analyze	Input/output constraints of NN, fully connected NN & MNIST classification, explainable AI via GenAI or worksheet, comparing CNNs to human perception, common students' conceptions about AI
Evaluate	Discuss risks: data quality, over/underfitting, adversarial attacks, variation handling, dataset requirements, misclassification issues and real-life implications
Create	Train a NN for facial expression recognition and create a Scratch program to use it for augmented reality face mask switching or designing a own program of similar complexity

Table 2: CNN teaching activities mapped to Bloom's Taxonomy levels.

Conclusion

The teaching approach described in this paper provides educators with knowledge about the functionalities and purposes of CNNs as well as practical guidance and resources for introducing Convolutional Neural Networks (CNNs) effectively into their classrooms. However, this is not the only valid way to teach CNNs. Educators are encouraged to adapt, modify, or selectively incorporate aspects of this approach based on their individual teaching styles, students' needs, and available resources. Although we deliberately chose accessible resources and examples, there is always room for improvement, adaptation, and creativity. We hope this paper inspires educators to explore and integrate CNNs into their teaching in ways that best suit their contexts. Future evaluations of this approach through classroom feedback, discussion or comparative studies could further refine and enhance its effectiveness.

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