

# Computer Vision Activities for the K–8 Mathematics Classroom emphasizing Feature Recognition using Teachable Machine

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Artificial intelligence (AI) technology includes machine learning. Machine learning involves the development of models that can learn and improve from data without being explicitly programmed. Machines analyze and interpret large amounts of data to identify patterns and make predictions. Computer vision (CV) uses machine learning focusing specifically on images. CV involves using algorithms to analyze visual images, performing tasks such as object detection, identifying shapes, and recognizing activities and locations in images. CVs enable computers to analyze and interpret visual data, allowing them to perceive and identify objects, faces, text, and other visual cues similar to the way humans do (Voulodimos et al., 2018). Because CV specifically focuses on the recognition of object detection and pattern recognition, there is a natural connection to mathematics. Mathematics often encourages learners to carefully evaluate patterns and make observations about features to discover and explain mathematical properties and relationships, CV technologies can enhance and support the evaluation of observed features, relationships, and patterns.

## Overview of TM Structure and Use

Using Google’s Teachable Machine (TM) as a CV technology, activities that emphasize the identification of mathematical features are described. TM is available as an open-source technology: <https://teachablemachine.withgoogle.com>. TM is designed for easy use and quick training; it is freely accessible, easy to navigate, and does not require programming experience (Toivonen et al., 2020). TM can classify items across a wide range of mathematics topics and grade levels with increased accuracy based on the number of training images uploaded. Recommendations and implications for mathematics teacher educators are discussed.

Generally, training an image classification model like TM consists of three steps: (1) collect images into a labeled training set, e.g., cats vs. dogs; (2) train the model via a computational process that analyzes the images; (3) test the model by showing it a new image to see if it classifies it correctly, e.g., recognizes a new cat is still a cat. TM is a simple point-and-click interface that allows users to build and test a new model in just a few minutes, simplifying the process. To build an image classification model using TM, students use the built-in webcam on their laptops to gather images to create a training data set. Alternatively, they can upload pre-existing image files. After collecting and labeling each category (class) of images, students press the button “Train Model.” Training time depends on the number of images and an individual computer’s processing power but is usually completed in under a minute. When training is complete, students test the model by using their webcam or by uploading new images

for the model to classify. The model returns a category (class) and a confidence value (given in a percentage). This immediate result gives students an opportunity to easily evaluate their model for successes and failures, so they can then quickly hypothesize and retrain their model to test methods of improving the accuracy of their models. We have developed several videos to guide explain image classification (<https://www.youtube.com/watch?v=KeJ2k5ovkNk>) and how to use of TM (<https://www.youtube.com/watch?v=vPKNhB3msBQ>). In addition to the image classification model, TM also offers an audio model for categorizing sounds and a pose model for categorizing body joint positions (see <https://www.youtube.com/watch?v=42XQvnxFJqA>).

### Additional Features

For advanced students or more technical lessons, hidden in the “Advanced” tab are options offering detailed control over the building of the model, including the number of Epochs, Batch Size, and Learning Rate. For longer-term projects, TM integrates with Google Drive to save training images and model outcomes. For short term projects, it is usually not necessary to save the training images, as you can export and either upload or download just the model for later use. For a video regarding saving and sharing your model, please see: <https://www.youtube.com/watch?v=vjfCzCQRxMo&t=13s>.

### Curriculum

While the curriculum for TM is not yet plentiful, such resources are growing. We have developed some curriculum that employs TM for sixth to eighth grades as part of a larger curriculum project on CV. Our project, ImageSTEAM, available at: <https://www.imagesteam.org>, provides an overview of middle school curriculum focusing on Artificial Intelligence, Computational Cameras, and Visual Media Curriculum. Lessons on engineering (STEM), English language arts/social studies, art and design, mathematics and science are available. There are various videos available that highlight how to use technologies as well as how the technologies actually work. There is also a lesson plan index.

### TM Mathematics Activities

When developing activities for use in mathematics, it is important to consider the purpose of CV technologies. CV technologies, like TM, are intended to identify and process objects similar to how the human eye processes objects. These design features have the potential to support students as they engage in a curriculum that emphasizes the identification of some features associated with mathematics content. At the kindergarten level, students can train TM to identify numbers by representing numbers both as written numerals (e.g., 4) and as objects (e.g., four color tiles or four bears). At the fourth-grade level, students might train TM to identify fractional values less than, more than, or equal to a benchmark (e.g.,  $\frac{1}{2}$ ). At the eighth-grade level, students can use TM to identify features of a function (e.g., increasing or decreasing, linear or nonlinear). Potential mathematics activities that use TM emphasizing the Common Core Mathematics Standards (CCMS) can be seen in Table 1 (National Governors Association, 2010). The described activities include a task description and a potential approach to the task.

**Table 1**  
*Sample TM Activities Based on CCMS*

Associated CCMS	Potential Task Using TM	Potential Approach using TM
<p>K.CC. Know number names and the count sequence: Write numbers from 0 to 20. Represent a number of objects with a written numeral 0-20.</p>	<p>Using both numerals and objects, challenge students to train TM to identify numbers in three categories: 4, 11, and neither.</p>	<p>Students can gather objects from around the classroom, and the teacher can upload images into three categories (4, 11, or neither). Written numbers can also be uploaded. Then, test TM to see if objects are correctly identified into one of the three categories.</p>
<p>4.NF. Extend understanding of fraction equivalence and ordering: Compare two fractions with different numerators and different denominators, e.g., by creating common denominators or numerators, or by comparing to a benchmark fraction such as <math>\frac{1}{2}</math>...</p>	<p>Using a variety of representations, train TM to identify fractional values in three categories: less than <math>\frac{1}{2}</math>, equal to <math>\frac{1}{2}</math>, and more than <math>\frac{1}{2}</math>. Iteratively test TM for accuracy and retrain as needed.</p>	<p>Students can represent fractions using manipulatives (e.g., fraction circles, fraction squares, color tiles (for a set model)) and drawings. Inevitably, TM will need to be retrained to improve its accuracy. The teacher should emphasize what features of the manipulatives or drawings should be adjusted to improve TM's accuracy.</p>
<p>8.F. Use functions to model relationships between quantities: Describe qualitatively the functional relationship between two quantities by analyzing a graph (e.g., where the function is increasing or decreasing, linear or nonlinear)...</p>	<p>Train TM to identify graphs in one of four categories: linear increasing, linear decreasing, nonlinear increasing, and nonlinear decreasing.</p>	<p>Using graph paper, students should draw at least three examples of each of the categories. Be sure that the drawings vary (e.g., line thickness, line color, quadrant location, and so on). After TM has been trained using all students' drawings, see if students can trick TM to identify a graph improperly, then retrain TM to improve accuracy.</p>

## Recommendations for Mathematics Teacher Educators

Sophokleous et al. (2021) conducted an analysis of CV in the K–12 classroom, emphasizing the intersection of robotics and CV. They found limited studies specifically focused on teachers and their use of CV technology. There is the potential for the technology to enhance learning, but when robots are used, cost is constraining. TM can mitigate associated CV costs because it is freely available. Kurz et al. (2021) provided professional development (PD) in AI and CV to middle school teachers. Using Personal Construct Theory, they analyzed changes in thinking using dendrograms. They found that teachers demonstrated a more sophisticated understanding of CV in STEM education as related to their pre- and post-dendrogram changes. Abichandani et al. (2023) researched the use of CV and AI with undergraduate engineering students ( $n = 153$ ). They found that using active learning techniques contextualized in AI and CV technology improved students' engagement. Challenges, like prior knowledge and skills, did impact learning experiences. Based on the limited research, there are several recommendations that may fruitfully support engagement with TM. One suggestion is the need for time to become familiar with TM features. Learners should be provided time to play with the technology to become familiar with features, and limitations. Second, while TM is generally user-friendly and intuitive, there is still a learning curve. Active learning techniques, including opportunities for learners to work with one another, can advance learning and engagement (Abichandani et al., 2023). Third, integrated STEM PD opportunities for teachers and learning experiences for preservice teachers should be offered to guide the use of CV in mathematics (Kurz et al., 2021). Overall, providing sufficient time and opportunities for hands-on practice is essential for teachers and learners to explore the features of TM.

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