Expanding Elementary School Computer Science Education with an Introduction to Machine Learning Through Rhythmic Studies

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ABSTRACT

Introducing elementary students to computer science and computational thinking (CS/CT) can enhance their problem solving skills and enhance their confidence and sense of belonging in computing. Project moveSMART aims to introduce learning activities into elementary classrooms that address computer science concepts in a way that integrates with core curriculum requirements and promotes physical activity. In this paper, we explore an extension to an initial set of Project moveSMART computer science learning activities to introduce elementary students to machine learning concepts in a way that is integrated with required learning objectives covered in a Physical Education course. Specifically, students use the BBC micro:bit and its on board sensors to capture rhythmic movement data, explore and analyze patterns in the data, and use a learned "dance move recognition" application that uses their data in order to learn about machine learning in an age appropriate way. To demonstrate feasibility of supporting dance move recognition on the resource-constrained device, we developed a prototype, which is able to detect 5 different dance moves with a 96.6% accuracy.

CCS CONCEPTS

• Social and professional topics → Computing education; **K-12 education**; **Computational thinking**; **• Human-centered computing → Ubiquitous and mobile computing systems and tools**;

KEYWORDS

wearable computing, activity recognition, smart health and well-being, computer science education, broadening participation in computing

ACM Reference Format:
Holly Hunter, Jamie Payton, and Christine Julien. 2023. Expanding Elementary School Computer Science Education with an Introduction to Machine Learning Through Rhythmic Studies. In *The Twenty-fourth International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing (MobiHoc '23), October 23–26, 2023, Washington, DC, USA.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3565287.3617623

MobiHoc '23, October 23–26, 2023, Washington, DC, USA

ACM ISBN 978-1-4503-9926-5/23/10…$15.00
https://doi.org/10.1145/3565287.3617623

1 INTRODUCTION

In the United States, physical activity levels are on the decline, and that decline starts to occur around age 8 or 9 [4]. This age is an imperative time to reintroduce students into physical activity in order to help them create and maintain healthy lifestyles. Maintaining a healthy lifestyle and having consistent physical activity is shown to positively correlate with academic success. As of 2020, 80% of adolescents fail to meet the recommended 60 minutes of physical activity a day [6].

Academic success is also shown to positively correlate with a foundational knowledge of computer science and computational thinking (CS/CT) skills and practices. However, computer science is not regularly taught in the academic school day, and at home, students may not have access to technology or the internet, which can be a barrier that serves to widen achievement gaps- when it comes to learning CS/CT. While many educators are in support of teaching CS/CT as part of the standard learning day in elementary classrooms, states often mandate curriculum standards educators have to meet, enforced through standardized tests, which do not include CS/CT learning objectives. In effect, this limits the amount of time that elementary educators can dedicate to CS/CT learning activities in the classroom.

We introduce Project moveSMART to address these challenges. Project moveSMART is a learning platform that includes CS/CT learning modules for 4th and 5th grade students that integrate CS/CT standards, increase physical activity levels, and satisfy core curriculum requirements [5]. Project moveSMART has been piloted in Texas elementary schools, and has deployed tutorials that address CS/CT concepts determined by the Computer Science Teaching Association (CSTA) and core curriculum concepts as defined by the Texas Essential Knowledge and Skills (TEKS) standards. To date, six tutorials on core CS/CT concepts have been implemented in 4th and 5th grade classrooms.

In this paper, we extend the Project moveSMART learning platform and curriculum to address the rapidly growing interest and need to educate students about machine learning and artificial intelligence. Specifically, we explore the feasibility of introducing learning activities that use the BBC micro:bit to capture physical movements performed by students while exploring rhythmic movement learning objectives as part of the required Physical Education curriculum, and using the physical activity data to exploring data analysis, pattern recognition, and machine learning as part of a lesson integrated with core subjects in a standard classroom. A key part of this work requires exploring the feasibility of a) collecting individual student's "dance move" data using the BBC micro:bit as a wearable device in order to plot and analyze data and b) deploying a machine learning algorithm on the resource-constrained BBC micro:bit to demonstrate a "dance move detector" application to students. We describe our proposed design of learning activities that incorporate machine learning and rhythmic movement and our approach for developing a machine learning "dance move detector" approach that supports the machine learning activity. Preliminary results demonstrate that it is feasible to achieve reasonable accuracy for dance move detection, with some limitations and practical considerations for implementation in a classroom.

2 BACKGROUND: PROJECT MOVESMART

Project moveSMART aims to broaden participation in computing by exposing children to CS/CT concepts in their elementary school years as part of the standard learning day. Because age appropriate CS/CT education is often an extracurricular or out-of-school activity, not all students have access to these opportunities; a lack of in-school access is particularly a concern given that girls, Black, and Hispanic students are underrepresented in computing [8]. Project moveSMART looks to break down structural barriers by introducing CS/CT into the standard learning day in elementary schools, providing access to students who would not otherwise have access to quality CS/CT education outside of school. Project moveSMART also aims to increase the amount of physical activity children receive in a school day, since physically active students tend to have higher levels of academic excellence [3]; integrating computing physical activity is also intended to spark student interest and engagement, demonstrating the connection of computing to students' own real-world experiences and context.

A pilot implementation and study in elementary classrooms for grades 4 and 5 in Austin, Texas shows that Project moveSMART is a promising approach for supporting student engagement in learning CS/CT. The pilot study of project moveSMART was a web based interactive cooperative game for 5th grade elementary classrooms in which students' activity levels progress their class along a map of the United States littered with "waypoints". Initially, students self classified their activity levels with a collection device with buttons that indicated their physical activity level. The more activity a class underwent, the faster they would move along the "waypoints". At each "waypoint" students learned about their correlating geography and history of the United States to meet core curriculum standards, and they would also be introduced to a new coding module with their own BBC micro:bit that runs Microsoft MakeCode. These tutorials would interact with their micro:bit in a way that encourages physical activity. For example, one lesson guided students through using a calibrated step counter, and then introduced a coding lesson to program the step counter using the MakeCode block-based programming language. After just one day of project moveSMART CS/CT education, students articulated that their perception of coding and coders had positively changed [5]. Over a 2 year period, students in classrooms using Project moveSmart curriculum increased their higher standardized testing scores in STEM subjects by 9% and their physical activity increased by 10 minutes per week [2], with Hispanic students having the greatest gains in physical activity at 13 additional minutes per week.

Currently, the Project moveSmart includes 7 lessons on CS/CT concepts: Hardware/Software concepts, sensing in computing systems, variables, control flow, rate with sub-concepts of data and analysis, complex conditionals, and communication between devices. As Project moveSMART expands, the research team has recognized the need for additional tutorials that address data science and machine learning on the micro:bit. An initial collection of data science tutorials [5], the micro:bit was used to support activity recognition for a small set of physical activities: standing, walking, and running with 99.7% accuracy in real time on the micro:bit [7]. This paper builds off of the existing Project moveSMART machine learning framework, but explores more complex activities that are aligned with the TEKS physical education requirements: rhythmic movements (i.e., dance moves).

3 PROPOSED SOLUTION: LIGHTWEIGHT DANCE RECOGNITION ON MICRO:BIT

To teach students about machine learning, the first step to implementation is collecting relevant student data. To meet TEKS physical education standards, students could meet rhythmic activity requirements and do data collection at the same time. For this tutorial, students would be introduced to a logging program on their micro:bit that would log their accelerometer data every 50ms while students performed a set of 5 dance moves. Students would learn about scientific data collection while meeting physical education standards. This tutorial sets the groundwork for the machine learning program, and starts introducing students to physical computing with their micro:bit.

After taking dance move data, this data can be visualized to connect student bodily movement to the data displayed. This tutorial would walk students through looking at their dance move data and extrapolating connections between their dance moves and the data presented. Example accelerometer data is shown in Figure 1. In the example accelerometer data, we can visually see 5 distinct sections, each corresponding to a different dance move as shown in Figure 1. In looking into this students can build their intuition of visually understanding data and patterns in data. After having some basic intuition about their data through visual pattern recognition, students can apply that knowledge to computers and machine learning. Students would learn that computers use pattern recognition to classify raw data into given classifications.

To ensure feasibility of implementing project moveSMART tutorials into the classroom, project moveSMART meets TEKS requirements. In this particular set of tutorials there are 3 standards that would be met in physical education, math, and science. In the TEKS physical education it states, "The physically literate student demonstrates competency in rhythmic activities and rhythmic combinations" [1] By incorporating the rhythmic aspect of dancing, the core curriculum standard is met. In the TEKS mathematics standards there is an entire section dedicated to data analysis [9], which directly correlates with the data collection and analysis aspect of the tutorials. As for the science concepts, students would interact with the tutorial in parallel with the scientific practices [10] of scientific observation and creating hypotheses based on their own data. Standards met can be seen in Figure 2.

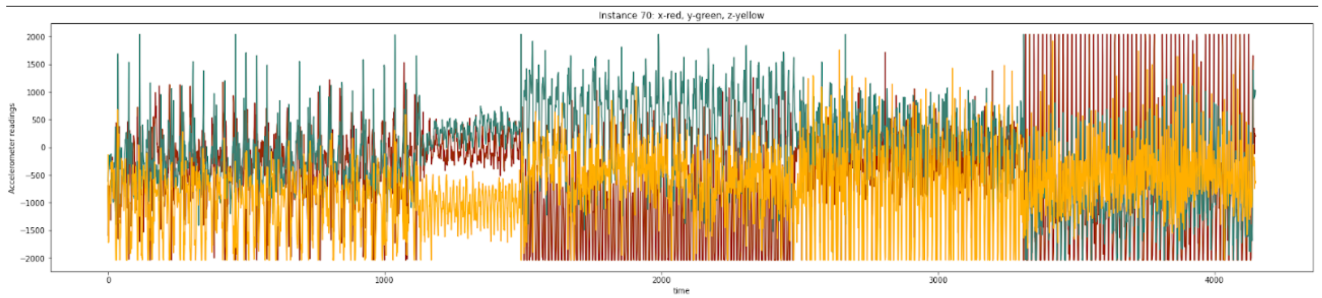

Figure 1: Example accelerometer data collected using a BBC micro:bit worn on the wrist by a user as they performed 5 distinct dance moves.

Learning Objectives	TEKS grade 4 standards	CSTA standards
Perform a series of rhythmic dance moves	Physical Education A(2): the physically literate student in the development of fundamental movement patterns, spatial and body awareness, and rhythmic activities	
Collect good accelerometer data and interpret data to find correlations in the data given and the movements they performed	Math 9: Data analysis: The student applies mathematical process standards to solve problems by collecting, organizing, displaying, and interpreting data.	1B-DA-07: Use data to highlight or propose cause-and-effect relationships, predict outcomes, or communicate an idea
Create hypothesis for how to get different data, and which movement could produce specific patterns in data	Science a(3): Scientific observations, inferences, hypotheses, and theories	1B-DA-06: Organize and present collected data visually to highlight relationships and support a claim.

Figure 2: Core curriculum concepts from the Texas Essential Knowledge and Skills Standards (TEKS) that are covered in the new Project moveSmart lessons that focus on dance move recognition.

4 FEASIBILITY OF DANCE MOVE RECOGNITION ON MICRO:BIT

To evaluate the feasibility of creating a dance move recognition application that could be implemented on the micro:bit and used in elementary classrooms, we collected data from a single participant who performed 5 dance moves while holding a BBC micro:bit in their dominant hand. The accelerometer data was sampled by the micro:bit every 50 ms. After data has been collected on the micro:bit, that data was pre-processed so that the data from the micro:bit is labeled with the corresponding dance move.

The dance moves are as follows:

- Move 1 is a "grapevine" in which the performer moves laterally, crossing one foot in front of the other, for two steps to one side and clapping the hands together
- Dance Move 2 is a "sweeping the floor" dance move with a side to side shuffle step while the arms are bent at the elbow with the fists stacked together held in the middle of the body and the arms are swung in this position from side to side
- Dance Move 3 is a rhythmic "ski hop" motion in which the legs are slightly bent with the hips angled with the arms initially positioned with the elbows bent and the fists raised at chest level and then are extended to a full position
- Dance Move 4 is part of the "All the Single Ladies" choreography, in which the user initially has the knees bent, leaning the front of the body forward with the arms extended toward the floor in front of the body, shifting one knees and pulling one elbow up toward the ribs repeatedly
- Dance Move 5 is an 80s inspired "The Wop" dance move, in which the arms are held out away from the body, bent at the elbow at a 90 degree angle, in an initial position with one hand pointing up and the other pointing down and then moving the hands forward and back in the frontal plan to alternate their positions while the performer shifts their head from side to side

We applied a supervised machine learning model to the data collected from the micro:bit in order to create a dance move detector that can be deployed for use in learning activities with students in elementary classrooms. In the choice of supervised learning algorithm, there are limitations to consider about the micro:bit. Due to its size and intended purpose, the micro:bit has a limit of 8KB of python script that can be written to the micro:bit, which limits the choice of learning model [7]. The machine learning model used is a support vector machine (SVM) with a linear kernel using a one vs. one decision classifier. Since an SVM is a supervised model, and we have labeled data, SVMs take numerical data (such as our processed accelerometer data) and then turn the numerical data into a class (which dance move is being performed). It can do all of this while being relatively lightweight to stay within the bounds of feasibility with the micro:bit.

We apply a per-person approach that results in a personalized dance move model. In other words, the data used to train the model was 100 instances of each dance move performed by a single person. Each dance move was performed 100 times for about 20-30 seconds each from a single person. We apply a 7:3 train/test split to train the SVM. With these parameters, the model performs with a 96.6% accuracy. Figure 3 shows the confusion matrix where where 0 is a grapevine with a clap, 1 is a sweeping the floor motion, 2 is a rhythmic ski hop, 3 is part of the "All the Single Ladies" choreograph, and 4 is an 80s inspired dance move.

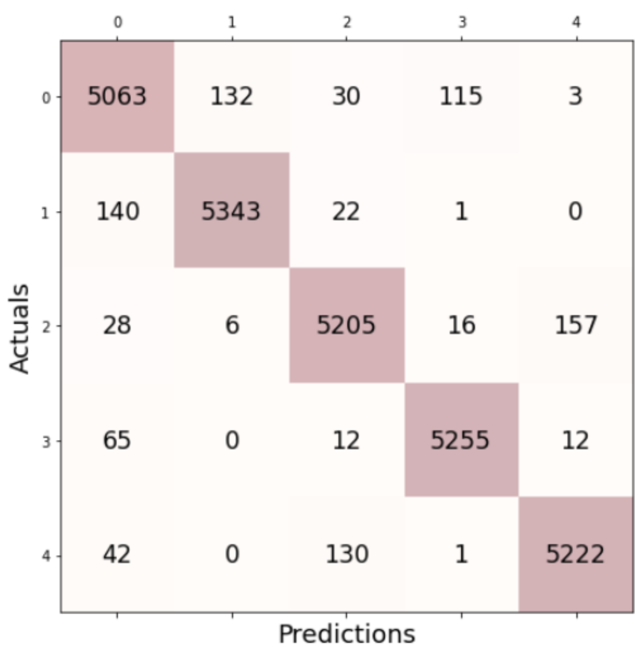

Figure 3: Confusion matrix for dance move prediction. Dance Move 1: Grapevine; Dance Move 2: Sweeping the Floor; Dance Move 3: Ski Hop; Dance Move 4: All the Single Ladies; Dance Move 5: 80s Inspired arm swings.

5 LIMITATIONS

subsectionTime to Collect Training Data To collect about 100 instances of data, it is estimated to take approximately 45 minutes for student data collection. This is assuming that an elementary school has about 20 students, they would each need to take 5 instances of data, and that each instance will take an upwards of 5 minutes. This time factors in instruction time and data collection but does not include any of the machine learning or data science instruction time. This restriction makes it difficult to execute in one classroom school day. However, this challenge could be mitigated if the data collection was dispersed throughout a school week, instead of a single day. Taking 10 - 15 minutes of data collection a day could be more feasible for students and educators.

5.1 Difference between student data and researcher data

We are also recognizing that the data provided to this model will be different from student data, since there are physiological differences in adult bodies versus children's bodies. The data collected was done in a controlled environment with a reasonably coordinated subject. The data collected from students could greatly vary in confidence and experience levels, and understanding that the environment could potentially not be as controlled as the research environment. To combat this, we would have to see how the model performs with student data, piloting this tutorial in classrooms.

5.2 Technology requirements

There is a required infrastructure and domain knowledge required to run a machine learning program, and this could be an undue burden on educators. Educators would have to run software, store/load student data into the program, and then run the machine learning program. For educators with little to no CS/CT experience this is a potential struggle. We propose adding a teacher facing interface to help with the technology requirements, or to have an undergraduate research student help educators in the classroom, as to aid in the machine learning process.

6 CONCLUSIONS

In this paper, we have introduced the foundations for Project moveSMART learning activities that teach students about data analysis, pattern recognition, and machine learning through the use of a wearable BBC micro:bit to capture and recognize dance moves as part of a TEKS-aligned Physical Education curriculum and TEKS-aligned lessons in math and science subjects in grades 4 and 5. We have explored the feasibility of using the BBC micro:bit as a wearable device for collecting dance move data and using the data to create a dance move detector application by creating a lightweight, supervised machine learning model using a support vector machine approach. Our evaluation shows that our prototype is capable of recognizing dance moves with 96.6% accuracy. While this single person model performs well, it is not currently deployed on the micro:bit to do dance move recognition in near real time. Future work would include taking the model and translating it into microPython to be sent to the micro:bit so it could perform locally on the micro:bit. To address time constraint limitations, a next step would be to change this model from a single person model to a group model that would need significantly less initial data. These changes would make the deployed tutorials go smoother and could potentially increase the accuracy for student data.

In future work, we plan to translate this model and framework into student tutorials to be deployed to partner elementary schools and evaluate changes in confidence and sense of belonging in computing as a result of exploring these moveSMART lessons, using pre and post-surveys for students. We also plan to explore how feasible it is for teachers to use these moveSmart learning activities in their classrooms, and evaluate how it went for educators through teacher interviews.

7 ACKNOWLEDGMENTS

This work is supported by the National Science Foundation under Grant No. 2050152 and Grant No. 2031324.

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