FaunaForest: A Novel Software Tool for Teaching Decision Trees to Middle School Students

Pragathi Durga Rajarajan, Adrian Cisneros, and Fred Martin
University of Texas at San Antonio, [pragathidurga.rajarajan, adrian.cisneros]@my.utsa.edu, fred.martin@utsa.edu

2025 IEEE Integrated STEM Education Conference (ISEC) | 979-8-3315-1343-6/25/$31.00 ©2025 IEEE | DOI: 10.1109/ISEC64801.2025.11147419

***Abstract* - Artificial intelligence literacy is fast becoming a foundational skill for students to develop as artificial intelligence technology rapidly advances and integrates further into key areas of society and everyday life. Artificial intelligence literacy involves understanding key concepts such as decision tree algorithms, which are essential for making informed decisions in numerous fields. To support K-12 curricula that foster artificial intelligence literacy, we developed a novel, easy-to-use software tool to teach middle school students about decision trees. We present FaunaForest, an interactive web application that allows students to complete decision tree puzzles, helping them learn what decision trees are and how they function. In this work, our research questions were: (RQ1) What evidence is there of learning within FaunaForest?; (RQ2) Are there any differences in learning outcomes between different grade levels?; and (RQ3) Is FaunaForest engaging? We collected and analyzed both quantitative and qualitative data. Our findings showed that students who played Level 3 of FaunaForest multiple times demonstrated a statistically significant improvement in performance compared to those who played it only once. Overall, the students enjoyed playing FaunaForest and made meaningful connections to ideas they had encountered before.**

Index Terms – AI Literacy, Artificial Intelligence, Decision Trees, K-12 AI Education

INTRODUCTION

As artificial intelligence (AI) technology rapidly evolves, people increasingly interact with AI in various forms and applications, such as voice assistants, recommendation algorithms, large language models, and social media filters [1]. This widespread adoption of AI across numerous key fields underscores the importance of developing AI literacy in children [2]-[5], along with basic computational and data literacy [6]. However, the *opaque boxes* of AI – where the inner workings are hidden from users – make it challenging for people to understand how AI applications function [7]. To better prepare children for success in a world that is increasingly shaped by AI technologies, it is critical to prioritize the development of AI literacy within K-12 students [8]-[9]. By demystifying these opaque boxes, we can help children gain a deeper understanding of AI algorithms and their workings [10].

To address this need, we developed FaunaForest, a software application that teaches middle school children the fundamentals of decision trees (DTs) through game-like activities. Its intuitive user interface and ability to collect quantitative data offer a novel way to engage students in AI education while supporting educators in the classroom. We elected to introduce DTs as they are more transparent and intuitive compared to complex models like neural networks [11], making them a more suitable starting point for introducing children to AI concepts.

In this work, our research questions were: (RQ1) What evidence is there of learning within FaunaForest?; (RQ2) Are there any differences in learning outcomes between different grade levels?; and (RQ3) Is FaunaForest engaging? While the project's scope limited the level of detail we could teach about DTs, the knowledge gained from this study provides valuable insights for advancing K-12 AI education research. Moreover, our tool can be easily used by educators to introduce middle schoolers to DTs within a short time frame during in-class sessions.

RELATED WORK

Casal-Otero et al. showed a significant increase in annual publications on K-12 AI literacy in recent years, highlighting a growing need for data in this area [12]. However, teaching AI concepts in a K-12 setting remains challenging, as the field continuously evolves, introducing new concepts and reshaping existing ones. Despite these challenges, DTs are a foundational concept widely used throughout AI and machine learning (ML), making them essential to teach. Decision tree (DT) algorithms have wide-ranging applications, including Chrime's work on an AI-powered medical diagnosis system for COVID-19 [13], Liu and Yang's data analysis and campaign optimization in marketing [14], and Munirathinam's work on predicting and improving the efficiency of operational maintenance [15]. Thus, the diverse applicability of DT algorithms across multiple industries makes it an important concept to introduce to children from a young age.

Furthermore, DTs are included in foundational education standards and recent work on K-12 AI education. Touretzky et al. outlined five "Big Ideas in AI" that need to be taught to all K-12 students [16]. DTs align closely with "Big Ideas" 2 ("Agents maintain models/representations of the world and use them for reasoning") and 3 ("Computers can learn from data"). AI4K12.org has also outlined a progression chart for each of these "Big Ideas," detailing what students at different grade levels should learn. DTs are discussed in these progression charts:

- Big Idea 2 Progression Chart [17]: Big Idea 2 Progression Chart [17]: Students in grades K-2 should understand that trees can be used to organize information. In grades 3-5, students should compare different classification algorithms (including DTs). By grades 6-8, students should recognize scenarios in which DTs would be too inefficient.
- Big Idea 3 Progression Chart [18]: Students in grades 3-5 should learn that DTs represent patterns as nodes and should create, traverse, and adjust the nodes to mimic how a DT model learns at a high level. By grades 6-8, students should understand in-depth how the DT model learns. Students in all grade levels should create datasets and use them to draw or train DTs.

The inclusion of DTs in multiple learning concepts in AI4K12.org's progression charts demonstrates the significance of DTs and the capability that K-12 students have to understand DTs.

Ma et al. created unplugged activities to teach middle schoolers about DTs, k-Nearest Neighbor, and AI bias [19]. Their use of the "PastaLand" activity, where students draw and test DTs for classifying pasta, showcased that the children gained a good understanding of DTs, highlighting the effectiveness of engaging activities. "PastaLand" was also used in [2, 20].

Lindner et al. developed unplugged activities to introduce students to various AI concepts [21]. Their "Good-Monkey-Bad-Monkey" game has students create efficient DTs for classifying monkeys. Testing this activity with students aged 14-16, they found that students could explain ML and make real-world connections, indicating that unplugged, game-based activities are effective.

Michaeli et al. outlined activities to teach 14-year-olds about DTs [22]. They adopted Lindner et al.'s "Good-Monkey-Bad-Monkey" game, had students complete a DT software project, and engaged them in discussions on AI/ML ethics. Observations showed that the students understood DTs, demonstrating the value of combining unplugged and coding-based activities.

Fleischer et al. taught middle schoolers about DTs by having the students construct them using data cards as part of an 8-lesson program [23]. Through interviews and observation, they found that the students could analyze the data cards and create strong DTs, highlighting the utility of thorough, unplugged activities.

In Broll and Grover's "AI and Cybersecurity for Teens (ACT)" curriculum for high schoolers, the "Twitter Bot Classification & Decision Tree Building" activity had students draw DTs, automatically generate DTs, and complete a DT coding project [24]. This demonstrated the potential scope for DT education in high school settings.

Multiple studies discussed enhancing undergraduate AI/ML classes with projects to improve student learning. Some of the mentioned DT projects include predicting contact lens type [25], creating an intelligent web browser with user models [26], and comparing the performance of different ML models on a dataset [27].

The substantial amount of work surrounding DT education demonstrates its significance, and further research in this area is needed. In our work, we created FaunaForest, a web application for quickly teaching DTs to middle school students. While Ma et al., Sanusi et al., Lindner et al., Michaeli et al., Fleischer et al., and Broll and Grover primarily employed unplugged activities or coding exercises for introducing DTs to children [19]-[24], we investigated the utility of a plugged approach. We explored software tools, focusing on a web-based approach, as they are easy to access via any web browser. Thus, they can be more easily integrated into lesson plans for middle school classrooms as they do not require complex setup. Furthermore, we incorporated the interactive and game-like approaches highlighted by Ma et al. and Lindner et al. in efforts to maximize student engagement and learning outcomes. FaunaForest is centered around interactive exercises so that students can develop a deeper understanding of DTs in an engaging format. FaunaForest also collects quantitative data on student interactions with it, addressing a gap in existing approaches that focus on observational and survey data for assessing student learning of DTs.

TOOL DESIGN

FaunaForest uses an interactive, game-like approach to teach DTs to middle school students. It was designed as a web-based application to make it widely accessible and easy to use in contexts beyond this study. For research purposes, FaunaForest collects quantitative data on student interactions with it, addressing a gap identified in many previous DT teaching approaches. The application can serve as a quick and engaging introduction to DTs. FaunaForest was implemented using HTML, CSS, and JavaScript. The source code is available at [28], and it is deployed at [29].

I. DT Puzzles

FaunaForest helps users learn DTs by solving interactive, animal-themed DT puzzles. Each puzzle consists of one or more decision nodes that present *yes-or-no* questions, leading to leaf nodes that contain different animals (classifications). Since the DTs are initially incomplete, users must complete them by filling in the missing decision nodes to match the provided classifications. For example, a DT puzzle with a height of one might start with a blank decision node, where the *yes* branch leads to a bird and the *no* branch leads to a dog. The user is prompted to consider various *yes-or-no* questions and select the one that correctly completes the DT. In the finished state, the correct question for the decision node should be *"Does it fly?"*

II. User Experience

First, the **Introduction Page** displays gameplay instructions and explanatory text introducing DTs.

Next, users encounter **Level 1**, where they work with DTs of height one. The decision node is blank, while the leaf nodes are provided. Users are given a list of possible yes-or-no questions to select from and place into the mystery decision node. After making their choice, users are given immediate feedback on correctness.

Level 2 (user interface shown in Figure I) is like Level 1, but instead, users encounter DTs of height two. Users must analyze the DT and determine the correct choice for two mystery decision nodes.

Next, users enter **Level 3**, a timed challenge level. Here, users have 90 seconds to complete as many DT puzzles of height 2 as possible and are encouraged to strive for high accuracy.

Each student completes at least one puzzle in Levels 1 and 2, and one round of Level 3, with the option to replay some or all FaunaForest levels multiple times.

III. Critical Thinking Required in FaunaForest

FaunaForest's DT puzzles require critical thinking, especially the more complex puzzles in levels 2 and 3. To determine which question to place in a decision node, students must carefully analyze which of the provided options properly differentiates the child nodes and ensure that the wording of the question matches the yes/no branches of the tree. For example, if a node's *yes* child is *tiger* and *no* child is *deer*, then *"Is it an herbivore?"* differentiates *tiger* and *deer* but does not match the yes/no branches. The correct answer would be *"Is it a carnivore?"*

Furthermore, when solving the top-most mystery node of a puzzle of height 2, students need to consider what differentiates the two leaf nodes on the left from the two leaf nodes on the right. This requires comparing the provided animals not just from the same decision node, but also across other decision nodes in the tree.

Therefore, even after understanding DTs and how they function, students will still need to think critically to complete these puzzles. This keeps FaunaForest engaging even after students gain a strong understanding of DTs.

Study Design

Including FaunaForest, seven projects developed during a research course for teaching AI concepts were tested with middle school students (grades 6–8) at a STEM public charter school in Texas. The racial demographics of students at this school are shown in Table I. IRB approval, parental consent, and student assent were obtained for this work. The projects were presented in an after-school program spanning two days, where interested students came to try out the projects to learn about different AI concepts. At the onset of each day's session, participants were given a pre-survey. Throughout the program, groups of students rotated to different projects every eight to ten minutes, allowing them to interact with multiple projects. However, due to time constraints, not all participants engaged with every project. Out of 122 participants, 72 interacted with FaunaForest.

For each group of students, we first provided an overview of FaunaForest. Then, we encouraged them to ask questions and play through each level multiple times to gain a strong understanding of DTs. The participants played through FaunaForest at their own pace and then completed an optional post-survey. Most students spent ~4.5 minutes with FaunaForest and ~5 minutes on the post-survey.

TABLE I
RACIAL DEMOGRAPHICS OF THE MIDDLE SCHOOL CHILDREN.

Race	Percentage
Asian	47 %
Hispanic/Latino	27 %
White	14 %
Black or African American	6 %
Two or More Race Categories	5 %
American Indian or Alaskan Native	< 1 %
Native Hawaiian or Other Pacific Islander	< 1 %

I. Data Collection

One **pre-survey** was administered to all participants to assess their initial familiarity with and attitudes towards AI. The pre-survey was not specific to FaunaForest only.

As participants used FaunaForest, **interaction data** was automatically collected by our web application. When a user enters FaunaForest, a file is created to store usage data on that particular user. These files were saved locally on the laptops the students used to interact with FaunaForest and later transferred to a secure cloud storage password-protected folder. For each completed puzzle, certain metrics were collected: timestamp, seconds spent, level, and accuracy. The accuracy is computed as *(correct selections) / (number of mystery nodes) x 100*. For each play of Level 3, additional summary data were collected: overall accuracy in Level 3 and the number of puzzles completed in Level 3. The overall accuracy in Level 3 averages the accuracy of each puzzle completed during Level 3.

Throughout the after-school program, the laptops used by students to interact with FaunaForest recorded both **audio and screen activity**. The audio recording served to collect discussions amongst participants or between the researchers and participants. The screen recording served as a thorough record of student interaction with FaunaForest.

After interacting with FaunaForest, the participants were provided with an optional **post-survey**. The post-survey items aimed to both gather feedback on FaunaForest and assess student learning outcomes.

II. Data Cleaning

Prior to data analysis, we performed data cleaning. On Level 3, some students discovered they could click *Next Puzzle* without completing the current puzzle and tried to progress through as many puzzles as possible without attempting them. Therefore, we discarded data for any puzzles completed in less than 5 seconds, as it takes more than 5 seconds to read all the options and drag/drop them into the mystery nodes. Additionally, we discarded FaunaForest interaction data for students who did not complete the post-survey. After data cleaning, we had complete pre-survey, FaunaForest interaction, and post-survey data for 51 students.

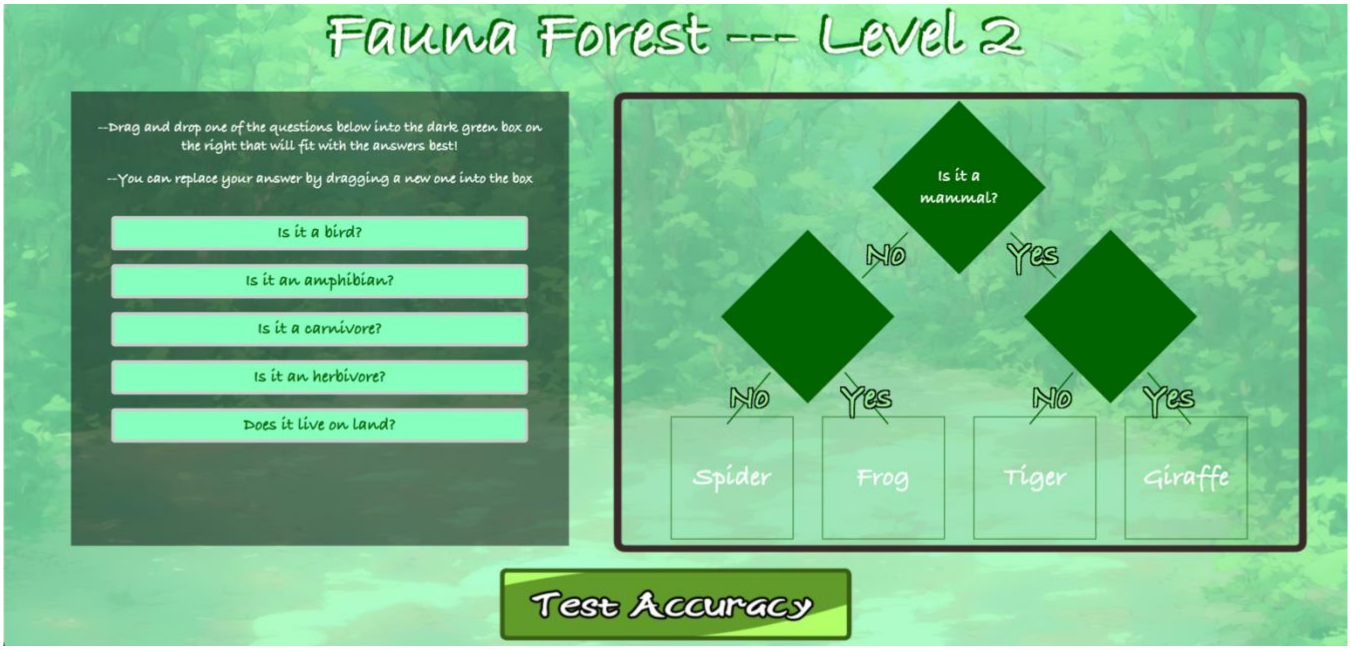

FIGURE I
USER INTERFACE OF LEVEL 2 OF FAUNAFOREST

RESULTS

After reviewing all of our quantitative and qualitative data, we found the FaunaForest interaction and post-survey data to be the most useful for answering our research questions.

I. (RQ1) What evidence is there of learning within FaunaForest?

To measure student learning, we first analyzed participants' overall average accuracy scores. Each student's score was calculated by averaging the accuracies of each puzzle they completed across all three levels. As shown in Figure II, many students performed well, with 74.5% achieving overall average accuracy scores of 70% or higher. Additionally, 12 students scored an overall average accuracy between 80-90%, and 23 students achieved scores between 90-100%.

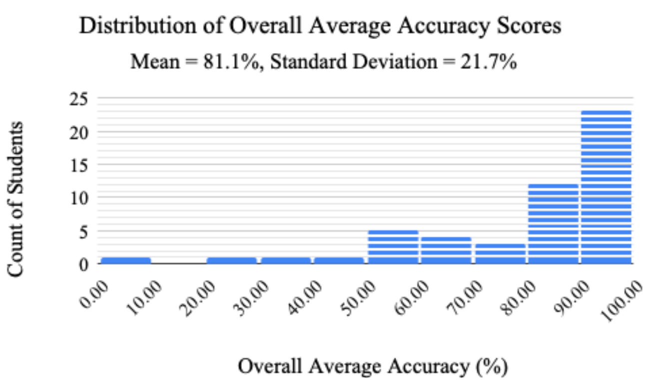

FIGURE II
DISTRIBUTION OF OVERALL AVERAGE ACCURACY SCORES

In addition, we analyzed the means of the student average accuracy scores across FaunaForest's three levels. The mean of students' average accuracy scores for each level was calculated by taking the mean of all students' average accuracy scores for that level. As shown in Table II, the mean increased as students progressed through FaunaForest, indicating an improved understanding of DTs. Despite the increasing difficulty of the levels, the rise in mean of students' average accuracy scores suggests that students were gaining a deeper understanding of DT structure as they engaged with the application.

TABLE II
MEAN AND STANDARD DEVIATION OF STUDENTS' AVERAGE ACCURACY SCORES ACROSS FAUNAFOREST'S 3 LEVELS.

	Level 1	Level 2	Level 3
Mean (%)	75.5	79.2	83.3
Standard Deviation (%)	37.9	30.7	21.5

An analysis of the number of times students played Level 3 versus their average accuracy for that level (as shown in Figure III) revealed that those who played Level 3 more than once performed better than those who played it only once. Figure III shows that most students with average accuracy scores of 50% or lower on Level 3 played it exactly once. To investigate further, we performed a two-sample t-test that compared the Level 3 average accuracy of students who played it once versus more than once. The t-test yielded a p-value of 0.044, so we conclude with 95% confidence that there is a significant difference in Level 3 average accuracy between students who played Level 3 once versus more than once. This suggests that playing Level 3 more than once significantly improves students' accuracy on DT puzzles.

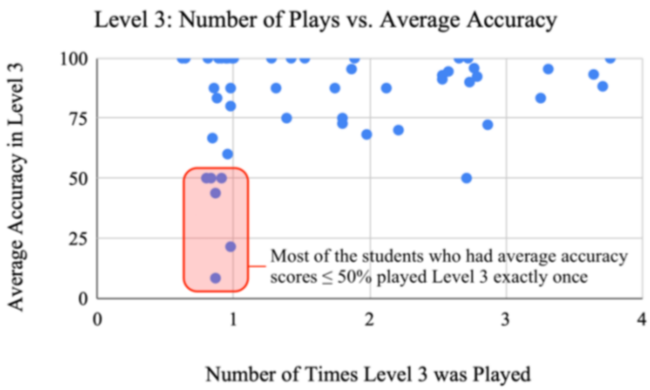

FIGURE III
THE NUMBER OF TIMES STUDENTS PLAYED LEVEL 3 VERSUS THEIR LEVEL 3 AVERAGE ACCURACY SCORES.

Separately, we analyzed responses to a post-survey item that presented a DT for classifying vehicles (shown in Figure IV) and asked how it would classify a bicycle. The correct answer was motorcycle. As per Table III, 72.3% of students answered this item correctly. This suggests that most students were able to successfully traverse a DT after interacting with FaunaForest, despite the application not explicitly teaching DT traversal.

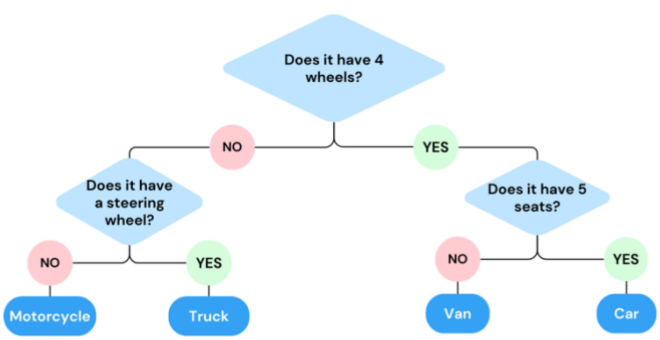

FIGURE IV
DT THAT WAS SHOWN IN THE POST-SURVEY DT TRAVERSAL ITEM. STUDENTS WERE ASKED TO DETERMINE HOW IT WOULD CLASSIFY A BICYCLE. RESPONSES ARE SHOWN IN TABLE III.

TABLE III
DISTRIBUTION OF RESPONSES TO THE POST-SURVEY MULTIPLE CHOICE DT TRAVERSAL ITEM. THE CORRECT ANSWER IS MOTORCYCLE.

Response	Percentage of Students
Motorcycle	*72.3%*
Bicycle	8.5%
Van	6.4%
Car	6.4%
Truck	6.4%

Additionally, we analyzed open-ended responses to the post-survey item that asked students to describe DTs. We identified six major categories of responses, as shown in Figure V, ranging from least to most insightful from left to right. Responses in the category *"Discuss flow charts, diagrams, or paths"* indicate an understanding of DT structure, while those in *"Use yes/no questions to identify something"* demonstrate comprehension of DT functionality. Responses categorized as *"Connected it to other concepts/ideas"* showcase a deep understanding of DTs, as these students made meaningful, accurate connections to related concepts. Out of 51 responses, 26 fell into the categories *"Discuss flow charts, diagrams, or paths," "Use yes/no questions to identify something,"* or *"Connected it to other concepts/ideas,"* indicating a strong understanding of DT structure and/or functionality. Additionally, five responses fell into the category *"Used to categorize things,"* demonstrating that these students had at least a basic understanding of DT applications.

II. (RQ2) Are there any differences in learning outcomes between different grade levels?

To address RQ2, we analyzed student performance across different grade levels. We first compared the overall average accuracy scores (discussed earlier) between students of different grade levels. As shown in Table IV, the mean overall average accuracy for grade 6 (77.0%) is slightly lower than that of grades 7 (82.5%) and 8 (86.3%).

TABLE IV
THE MEAN AND STANDARD DEVIATION OF OVERALL AVERAGE ACCURACY SCORES BY GRADE LEVEL.

Grade	Count of Students	Mean	Standard Deviation
6	18	77.0%	21.7%
7	26	82.5%	23.3%
8	7	86.3%	15.6%

Additionally, 7th and 8th graders performed better than 6th graders on the post-survey DT traversal item (shown in Figure IV). As per Table V, 50% of 6th graders answered correctly, compared to 76.9% of 7th graders and 85.7% of 8th graders. However, the sample size was too small to determine a statistically significant difference in performance between grade levels.

TABLE V
PERFORMANCE ON POST-SURVEY DT TRAVERSAL ITEM BY GRADE LEVEL.

Grade	Correct Responses	Incorrect Responses
6	9 (50%)	9 (50%)
7	20 (76.9%)	6 (23.1%)
8	6 (85.7%)	1 (14.3%)

III. (RQ3) Is FaunaForest engaging?

To determine which features students found most useful, we analyzed responses to the post-survey item, *"What features of the tool did you find useful?"* Students were allowed to select multiple options and type in their own responses. As shown in Table VI, 36 out of 51 students selected "Interactive Activities" as one of the most useful features. This indicates that the interactive nature of FaunaForest was the most appreciated and impactful aspect. Additionally, many participants selected "Explanatory Text" and "Visualizations," suggesting that the combination of explanations, visualizations, and interactive puzzles all likely contributed to their learning.

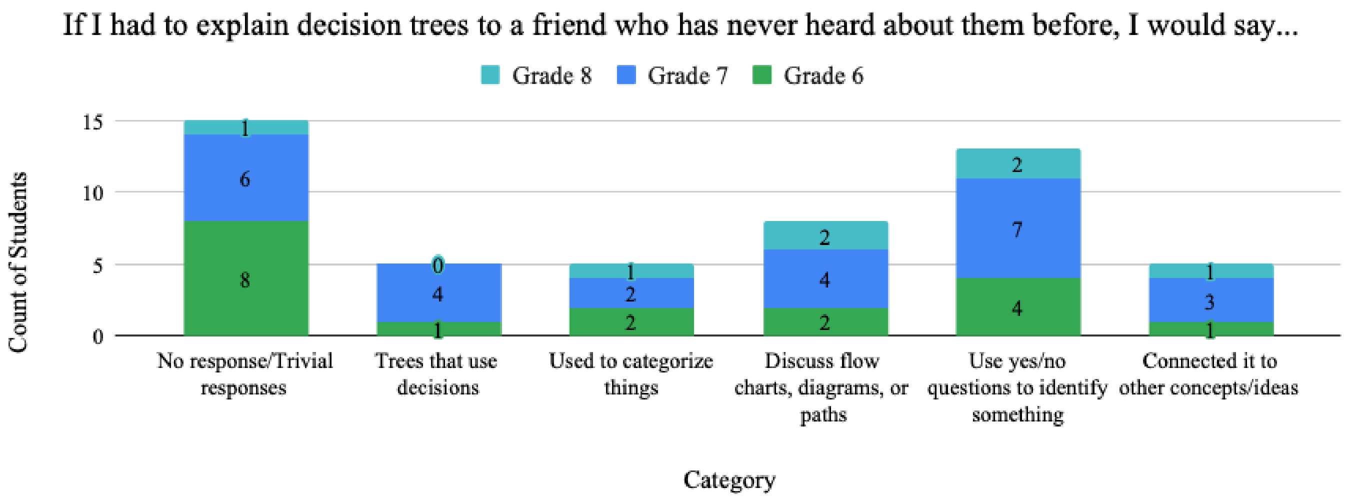

FIGURE V
CATEGORIZED RESPONSES TO POST-SURVEY OPEN-ENDED ITEM ASKING STUDENTS HOW THEY WOULD DESCRIBE DTS TO A FRIEND.

TABLE VI
FEATURES STUDENTS FOUND USEFUL IN FAUNAFOREST. (STUDENTS COULD SELECT MULTIPLE OPTIONS (FROM INTERACTIVE ACTIVITIES, EXPLANATORY TEXT, AND VISUALIZATIONS) AND/OR TYPE IN THEIR OWN RESPONSES.)

Response	Count of Students
Interactive Activities	36
Explanatory Text	29
Visualizations	23
"My Intellect"	2
"Nothing"	1

We also observed some participants express enjoyment with FaunaForest, with select accounts described here:

- One student particularly enjoyed Level 3 and chose to stay at our table for the remainder of the after-school session instead of rotating to other applications.
- During the first session, one student initially expressed confusion but was assisted by us. At the next session, she returned with a friend to play FaunaForest together.
- Many students enjoyed the engaging game-like structure of Level 3 and competed to see who could get the highest accuracy scores.

DISCUSSION

With FaunaForest, students learned about DTs by solving DT puzzles. After interacting with FaunaForest, most students developed a sufficient understanding of DTs, as demonstrated by their ability to complete DT puzzles with solid accuracy. Drawing inspiration from traditional grading rubrics, we categorized students' understanding of DTs into three levels: "adequate," "good," and "strong," based on their overall average accuracy scores. Specifically, an average accuracy score between 70-80% indicates an "adequate" understanding, 80-90% represents a "good" understanding, and 90-100% reflects a "strong" understanding. According to these criteria, 74.5% of students achieved an overall average accuracy above 70%, reflecting at least an "adequate" understanding of DTs. Additionally, 12 students obtained an average accuracy score between 80–90%, indicating a "good" understanding of DTs. Notably, 23 students achieved an average accuracy above 90%, demonstrating a "strong" understanding. Furthermore, students' average accuracy scores increased as they progressed through FaunaForest, from a mean of 75.5% at Level 1 to 79.2% at Level 2 and 83.3% at Level 3. This upward trend suggests that as students progressed through FaunaForest, they completed DT puzzles with increasing accuracy. Despite the growing difficulty of DT puzzles at each successive level, students' improving accuracy indicates a strengthened understanding of DTs through continued interaction with FaunaForest. In addition, a two-sample t-test found that students who played the timed challenge level multiple times performed better on DT puzzles compared to those who played it once. Additionally, although FaunaForest does not explicitly teach DT traversal, 72.3% of students still correctly answered a DT traversal item on the post-survey. This suggests that the DT puzzles in FaunaForest helped foster an understanding of how DTs are traversed to make decisions. Additionally, students' open-ended responses about DTs were detailed and thorough. Specifically, 8 students demonstrated an understanding of DT structure by comparing them to similar concepts, such as flowcharts. Out of 51 students, 13 described DT functionality well, explaining how DTs utilize *yes-or-no* questions to identify various entities. Furthermore, 5 students connected DTs to familiar concepts from other contexts, such as dichotomous keys (used in biology/ecology to classify organisms) and *Akinator* (a game in which a computer asks a series of *yes-or-no* questions to determine the user's thoughts). These responses suggest that some middle schoolers comprehended DTs well enough to make accurate, thoughtful connections to concepts from their daily lives, further demonstrating their understanding.

We also found that the students in grades 7 and 8 performed better than those in grade 6. One potential reason for this difference is that the 7th and 8th grade curriculum at the study's school may provide stronger preparation for the critical thinking skills required to complete FaunaForest puzzles. Additionally, 7th and 8th graders are exposed to a broader curriculum with more advanced topics, including dichotomous keys in biology and greater familiarity with various animal species. These factors may have better equipped 7th and 8th graders to solve the DT puzzles in FaunaForest.

In addition, our findings demonstrate that engaging software applications can be created to effectively teach DTs, as participants enjoyed FaunaForest's game-like, interactive approach. For instance, 36 out of 51 participants identified interactivity as one of the key features they found useful. Additionally, we observed that the competitive nature of the timed Level 3 led to high student engagement and excitement, highlighting the effectiveness of creating competitive activities in enhancing student participation.

Overall, our findings indicate that FaunaForest successfully engages middle school students in learning about DTs. Many students enjoyed interacting with our application, especially the timed challenge level. Our work supports the previous research by Ma et al. and Lindner et al. [19, 21], that interactive activities are effective for teaching students about DTs.

In addition, FaunaForest does not require any prior coding knowledge, making it an effective tool for introducing children to the foundational concepts of DTs. Unlike previous studies that primarily used unplugged activities or coding activities [19]-[24], we employed a software tool for teaching DTs. Our findings demonstrate the usefulness of software tools in introducing AI concepts to middle school children.

Web-based applications, like FaunaForest, do not require technical expertise for installation or use, making them convenient for educators to integrate into in-classroom AI education. Furthermore, we found that FaunaForest fostered an understanding of DTs in a short timeframe, as most students interacted with the application for only about 4.5 minutes. This suggests that FaunaForest can easily be used as a quick introduction to DTs in AI education initiatives for middle school children and can be supplemented with additional materials to foster a deeper understanding.

LIMITATIONS

Due to time constraints, we were unable to do a pre-survey versus post-survey analysis for FaunaForest. As a result, we lacked information on students' pre-existing knowledge of DTs before interacting with FaunaForest. Conducting a study of FaunaForest that includes a pre- versus post-survey analysis could provide deeper insight into student learning of DTs.

FUTURE WORK

The sample size was limited in this study, so we need to test FaunaForest with more students. In addition, evaluating FaunaForest with a pre- versus post-survey analysis could provide more insight.

Recognizing that middle school students have the potential to grasp AI concepts, there is an opportunity to introduce more complex concepts while simultaneously enhancing the original design of FaunaForest to improve the teaching experience. One improvement could be to add more dynamic interactions, such as additional levels or allowing users to build their own DTs. This could make the overall experience more interactive and engaging.

While the animal theme was selected to pique the interest of the students, we can expand FaunaForest to include other themes and allow users to select the themes they are most interested in.

FaunaForest can also be adapted for elementary and high school students by tailoring its structure and difficulty to different age groups.

CONCLUSION

In this study, we developed FaunaForest, an interactive web application designed to teach decision trees, and tested it with middle school students in an after-school program. To keep students engaged and enhance their overall learning experience, we incorporated an interactive, game-like approach with accuracy scores and a timed third level. Our work highlights the potential of using software tools to teach AI concepts to children. Specifically, our findings indicate that students could understand the structure of DTs and how they function after using our tool. Using a two-sample t-test, we found a statistically significant result indicating that participants who played Level 3 of FaunaForest more than once performed better than those who played it only once. Notably, most participants developed at least an adequate understanding of DTs, with 26 out of the 51 participants developing a strong understanding, as evidenced by their thorough open-ended descriptions of DTs. Overall, FaunaForest proved effective in fostering an understanding of DTs in the students and can be adopted by educators for use with K-12 AI education initiatives.

ACKNOWLEDGMENT

We are grateful to our peers in the University of Texas at San Antonio's research course *Developing AI Tools for K-12* for their feedback during the development of FaunaForest. We would like to thank the administrators and staff who made the after-school sessions possible. We also thank the students who participated in the study. This material is based upon work supported in part by the National Science Foundation under Grant IIS-2112633.

REFERENCES

[1] Lee, Clifford H., Gobir, Nimah, Gurn, Alex, et al. 2022. "In the Black Mirror: Youth Investigations into Artificial Intelligence." ACM Trans. Comput. Educ. 22 (3). https://doi.org/10.1145/3484495.

[2] Lee, Irene, Ali, Safinah, Zhang, Helen, et al. 2021. "Developing Middle School Students' AI Literacy." In Proceedings of the 52nd

ACM Technical Symposium on Computer Science Education, pp. 191–97. https://doi.org/10.1145/3408877.3432513.
[3] Lipovec, Alenka. 2024. "Charting the Path Forward: Effective Didactic Approach for Teaching AI Literacy in K-12 Education." In 2024 13th Mediterranean Conference on Embedded Computing (MECO), pp. 1–4. https://doi.org/10.1109/MECO62516.2024.10577894.
[4] Van Brummelen, Jessica, Heng, Tommy, and Tabunshchyk, Viktoriya. 2021. "Teaching Tech to Talk: K-12 Conversational Artificial Intelligence Literacy Curriculum and Development Tools." Proceedings of the AAAI Conference on Artificial Intelligence 35 (17), pp. 15655–63. https://doi.org/10.1609/aaai.v35i17.17844.
[5] Yau, King Woon, Chai, Ching Sing, Chiu, Thomas K. F., et al. 2022. "Developing an AI Literacy Test for Junior Secondary Students: The First Stage." In 2022 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE), pp. 59–64. https://doi.org/10.1109/TALE54877.2022.00018.
[6] Grover, Shuchi. 2024. "Teaching AI to K-12 Learners: Lessons, Issues, and Guidance." Proceedings of the 55th ACM Technical Symposium on Computer Science Education (SIGCSE 2024), pp. 422–28. https://doi.org/10.1145/3626252.3630937.
[7] Long, Duri, and Magerko, Brian. 2020. "What Is AI Literacy? Competencies and Design Considerations." In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20), pp. 1–16. https://doi.org/10.1145/3313831.3376727.
[8] Akram, Bita, Yoder, Spencer, Tatar, Cansu, et al. 2022 "Towards an AI-Infused Interdisciplinary Curriculum for Middle-Grade Classrooms." Proceedings of the AAAI Conference on Artificial Intelligence, 36 (11), pp. 12681–88. https://doi.org/10.1609/aaai.v36i11.21544.
[9] Touretzky, David, Gardner-McCune, Christina, and Seehorn, Deborah. 2022. "Machine Learning and the Five Big Ideas in AI." International Journal of Artificial Intelligence in Education, 32(3), pp. 547-543 https://doi.org/10.1007/s40593-022-00314-1.
[10] Hitron, Tom, Orlev, Yoav, Wald, Iddo et al. 2019. "Can Children Understand Machine Learning Concepts? The Effect of Uncovering Black Boxes." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, (CHI '19), pp. 1-11. https://doi.org/10.1145/3290605.3300645.
[11] Guidotti, Riccardo, Monreale, Anna, Ruggieri, Salvatore, et al. 2018. "A Survey of Methods for Explaining Black Box Models." ACM Comput. Surv. 51 (5). https://doi.org/10.1145/3236009.
[12] Casal-Otero, Lorena, Catala, Alejandro, Fernández-Morante, Carmen, et al. 2023. "AI Literacy in K-12: A Systematic Literature Review." International Journal of STEM Education 10 (1), p. 29. https://doi.org/10.1186/s40594-023-00418-7.
[13] Chrimes, Dillon. 2023. "Using Decision Trees as an Expert System for Clinical Decision Support for COVID-19." Interactive Journal of Medical Research, 12, p. e42540. https://doi.org/10.2196/42540.
[14] Liu, Yi, and Yang, Shuo. 2022. "Application of Decision Tree-Based Classification Algorithm on Content Marketing." Journal of Mathematics, 2022, pp. 1-10. https://doi.org/10.1155/2022/6469054.
[15] Munirathinam, Srikanth. 2021. "A Novel Decision Support System for Managing Predictive Maintenance Strategies Based on Machine Learning Approaches." Reliability Engineering and System Safety 214:107587.
[16] Touretzky, David, Gardner-McCune, Christina, Martin, Fred, et al. 2019. "Envisioning AI for K-12: What Should Every Child Know about AI?" Proceedings of the AAAI Conference on Artificial Intelligence, 33, (1), pp. 9795–9799. https://doi.org/10.1609/aaai.v33i01.33019795.
[17] ai4k12.org. 2021. "Big Idea #2: Representation and Reasoning." June 2021. https://ai4k12.org/wp-content/uploads/2022/03/AI4K12-Big-Idea-2-Progression-Chart-Working-Draft-of-Big-Idea-2-v.06.28.2021_v3.pdf.
[18] ai4k12.org. 2020. "Big Idea #3: Learning." November 2020. https://ai4k12.org/wp-content/uploads/2021/01/AI4K12-Big-Idea-3-Progression-Chart-Working-Draft-of-Big-Idea-3-v.11.19.2020.pdf.
[19] Ma, Ruizhe, Temitayo Sanusi, Ismaila, Mahipal, Vaishali, et al. 2023. "Developing Machine Learning Algorithm Literacy with Novel Plugged and Unplugged Approaches," (SIGCSE 2023), pp. 298–304. https://doi.org/10.1145/3545945.3569772.
[20] Sanusi, Ismaila Temitayo, Sunday Oyelere, Solomon, Vartiainen , Henriikka, et al. 2023. "Developing Middle School Students' Understanding of Machine Learning in an African School." Computers and Education: Artificial Intelligence, 5, p. 100155. https://doi.org/10.1016/j.caeai.2023.100155.
[21] Lindner, Annabel, Seegerer, Stefan, and Romeike, Ralf. 2019. "Unplugged Activities in the Context of AI." In Informatics in Schools. New Ideas in School Informatics, Edited by Sergei N. Pozdniakov and Valentina Dagienė, pp. 123–35.
[22] Michaeli, Tilman, Seegerer, Stefan, Kerber, Lennard, et al. 2023. "Data, Trees, and Forests-Decision Tree Learning in K-12 Education." In The Third Teaching Machine Learning and Artificial Intelligence Workshop, pp. 37–41.
[23] Fleischer, Yannik, Podworny, Susanne, and Biehler, Rolf. 2024. "Teaching and Learning to Construct Data-Based Decision Trees Using Data Cards as the First Introduction to Machine Learning in Middle School," *Stat. Educ. Res. J.*, vol. 23, pp. 3, Aug. 2024, doi: 10.52041/serj.v23i1.450.
[24] Broll, Brian, and Grover, Shuchi. 2023. "Beyond Black-Boxes: Teaching Complex Machine Learning Ideas through Scaffolded Interactive Activities." Proceedings of the AAAI Conference on Artificial Intelligence 37 (13), pp. 15990–15998. https://doi.org/10.1609/aaai.v37i13.26898.
[25] Sun, Wenqian, and Gao, Xing. 2018. "The Construction of Undergraduate Machine Learning Course in the Artificial Intelligence Era." In 2018 13th International Conference on Computer Science & Education (ICCSE), pp. 1–5. https://doi.org/10.1109/ICCSE.2018.8468758.
[26] Markov, Zdravko, Russell, Ingrid, Neller, Todd, et al. 2005. "Enhancing Undergraduate AI Courses through Machine Learning Projects." In Proceedings Frontiers in Education 35th Annual Conference, p. T3E-21. https://doi.org/10.1109/FIE.2005.1611941.
[27] De Barros, Vitor Augusto Menten, Mohallem Paiva, Henrique, and Takashi Hayashi, Victor. 2023. "Using PBL and Agile to Teach Artificial Intelligence to Undergraduate Computing Students." IEEE Access, 11, pp. 77737–77749. https://doi.org/10.1109/ACCESS.2023.3298294.
[28] Engaging Computing Group. 2024. "FaunaForest Github Repository." [Online]. Available: https://github.com/engaging-computing/FaunaForest
[29] Rajarajan, Pragathi Durga, Cisneros, Adrian, and Martin, Fred. 2024. "FaunaForest Live Link." [Online]. Available: https://engaging-computing.github.io/FaunaForest/

AUTHOR INFORMATION

Pragathi Durga Rajarajan, Undergraduate Student, Department of Computer Science, University of Texas at San Antonio.
Adrian Cisneros, Undergraduate Student, Department of Computer Science, University of Texas at San Antonio.
Fred Martin, Professor and Chair, Department of Computer Science, University of Texas at San Antonio.