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AI-Powered Data Structure and Algorithm Visualization Using Large Language Models (LLM)

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Abstract **- Data Structures and Algorithms (DSA) are the backbone of computer science education; still, traditional learning methods based on static code examples and slide-show lectures are ineffective in communicating the step-by-step dynamic process of algorithms. This drawback makes it difficult for students to form correct mental images of algorithmic processes, leading to passive learning and superficial understanding. Recent breakthroughs in Artificial Intelligence (AI), specifically Large Language Models (LLMs), open new avenues for developing intelligent and interactive learning environments that adapt to the needs of individual learners and allow multiple modalities of interaction.**

This paper introduces the conceptualization and design of AlgoVista, an AI-augmented algorithm learning platform that combines real-time visualizations of algorithms with adaptive explanations and interactive assessments using LLMs. The proposed system combines a MERN-stack web interface with Python algorithm execution, an LLM for context-dependent explanations, and a text-to-speech system for audio narration. As algorithms run step by step, the system dynamically produces plain-language explanations for each state transition and provides short-form personalized quizzes based on the learner's past interactions and mistakes.

AlgoVista, by integrating deterministic algorithm execution, multimodal explanation, and learner-centric assessment in a unified framework, seeks to convert passive algorithm demonstrations into active learning experiences.The proposed architecture remedies the major shortcomings of existing visualization systems by allowing adaptability, interactivity, and continuous feedback, which help to facilitate conceptual understanding and learning outcomes in Data Structure and Algorithm education.

I. INTRODUCTION

Data Structures and Algorithms (DSA) are the fundamental constituents of computer science and software engineering education. Understanding DSA is required for effective problem-solving, program optimization, and designing scalable and robust systems. As such, DSA has always been an essential component of computer science education in academic institutions. However, despite its significance, the concepts of DSA are perceived as difficult and abstract by students, particularly at the introductory level.

The primary cause of this difficulty is the nature of traditional teaching methods. Traditional teaching methods are based on static code examples, illustrations in textbooks, and theoretical discussions, which fail to offer a correct representation of the dynamic nature of algorithms during the execution process. Algorithmic processes involve sequential and recursive transformations of data, conditional statements, loops, and recursion, which are all dynamically involved and cannot be correctly visualized in the mind. Thus, most students face difficulties in creating correct mental models of algorithmic processes and tend to learn them mechanically instead.

To address these difficulties, algorithm visualization systems have been designed as an effective teaching aid. These systems represent algorithms graphically and animatically, allowing students to visualize the process in an intuitive manner.As a result, many students find it difficult to develop a solid mental model and are more prone to memorizing learning than conceptual comprehension. In order to address this problem, algorithm visualizations have been used extensively. Students can watch the process in real time thanks to visualization tools that use animations and pictures to show how algorithms operate.

Visualizations can improve procedural comprehension and engagement, according to earlier educational research. Nevertheless, the visualization tools that are now available can only offer static explanations and pre-made animations. They are less effective in a learning setting because they are unable to adjust to the needs of specific pupils, misconceptions, and differences in prior knowledge. New potential to lessen these difficulties have been made possible by developments in artificial intelligence (AI), especially large language models (LLMs).

However, despite the above developments, there still exists a large gap in the current status of educational systems. Most of the current educational systems either focus on the visualization of deterministic algorithms without the use of intelligent explanations or rely on AI-based explanations that are ungrounded in the actual execution of algorithms. This creates a paradox regarding the correctness of explanations, educational reliability, and learning efficiency. Additionally, there are very few systems that utilize real-time learning assessments to check the understanding of the learner and adjust the learning process accordingly.

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This duality leads to concerns regarding the validity of explanations, educational reliability, and efficiency of learning. Furthermore, there are very few systems that incorporate real-time learning assessments to validate the understanding of the learner and adjust the learning process accordingly.It is in the context of the above challenges that this research paper explores the conceptualization of an AI-driven algorithm learning system that incorporates deterministic execution of algorithms with adaptive explanations and learning assessments based on LLMs. The objective of this research paper is to bridge the existing gap between visualization systems and intelligent tutoring systems by conceptualizing a learner-friendly system that can enhance conceptual understanding, engagement, and retention in the context of DSA learning.

II. LITERATURE SURVEY

Teaching and learning of Data Structures and Algorithms (DSA) have been known to be challenging because of their abstract concepts and dependency on dynamic execution processes. Over the years, several methods have been proposed to enhance conceptual understanding, starting from visualizing algorithms to adaptive learning systems and, more recently, AI-based learning platforms. This section discusses the existing literature on visualizing algorithms, educational artificial intelligence, and the use of Large Language Models in computer science education.

A. Algorithm Visualization Techniques:

Algorithm visualization has been extensively researched as a valuable teaching tool for bettering learners' comprehension of algorithmic processes. Traditional algorithm visualization systems were based on graphical animation techniques that showed step-by-step transformations of data structures during the execution of an algorithm.

Visualization tools such as VisuAlgo and PythonTutor enable learners to visualize the step-by-step transformations of variables, arrays, trees, and graphs. Studies conducted by Halim et al. showed that visualizations greatly improved learners' procedural understanding and decreased cognitive loads compared to text-based descriptions.

However, despite the benefits of visualization, several studies have pointed out the shortcomings of current visualization tools. Most current visualization tools are based on static or pre-written descriptions that fail to adjust to the learners' level of proficiency.

Moreover, current visualization tools tend to focus more on the "how-to" aspect of an algorithm but lack the ability to explain the "why" part of the algorithm. This results in learners being able to understand the execution process of an algorithm but failing to comprehend the underlying concepts of time complexity, decision-making, or optimization.

B. Adaptive Learning and Educational AI Systems:

Adaptive learning systems aim to offer personalized educational content based on the behavior and performance of the learners. Based on previous studies in educational AI, adaptive learning has been proven to improve the retention and engagement of learners by adapting levels of difficulty and explanation complexity. Studies conducted by organizations such as MIT and Stanford have emphasized the success of multimodal learning environments that combine text, image, and audio-based content.

The traditional adaptive learning system, on the other hand, uses rule-based models and predetermined learning paths. The system is rigid in its capacity to generate natural language explanations and is highly dependent on human intervention in designing educational content. While successful to a point, the system is not scalable for various topics and learners, especially in technical fields such as DSA.

C. Role of Large Language Models in Education:

The advent of Large Language Models has brought about a paradigm shift in the field of intelligent tutoring systems. LLMs have the ability to comprehend programming logic, as well as provide step-by-step

Research carried out by Anderson et al. has shown that tutoring systems based on LLMs can bring about a marked improvement in the confidence and conceptual understanding of learners. At the same time, this research also points out the important challenges faced by LLMs, such as sometimes being inaccurate, "hallucinating" explanations, and a lack of alignment with deterministic program execution. Working alone, LLMs can sometimes provide explanations that are correct-sounding but not necessarily aligned with the actual algorithmic behavior.

D. Hybrid Systems: Integration of Visualization and LLMs:

The recent literature in the field indicates that the combination of LLMs with deterministic visualization systems can overcome the shortcomings of both methods. Visualization helps in ensuring correctness and traceability, while LLMs help in providing adaptive and human-like explanations. There are very few existing systems that have tried to integrate visualization and LLMs, and most of them are still at the conceptual or prototype level.

The current state of research in the field does not have comprehensive frameworks that help in synchronizing traces of algorithm execution with explanations, audio narration, and assessment provided by LLMs. Moreover, most of the platforms do not have real-time quizzes or feedback systems that are directly connected to the visualization process.

E. Identified Research Gaps:

From the literature reviewed, the following research gaps have been identified:
1. There is a lack of adaptive AI explanations that are synchronized with the visualization of the algorithm
2. There is a lack of multimodal learning support that is a combination of text, animation, and speech
3. There is a lack of real-time assessment and feedback
4. There is a lack of validation methods to validate the reliability of LLM explanations

III. METHODOLOGY

A. Mathematical Formulation

The proposed system can be modeled as a tuple:

$$S = \{U, A, D, V, E, Q, F\}$$

where:

- $U = \{u_1, u_2, \ldots, u_n\}$ is the set of users (learners)
- $A = \{a_1, a_2, \ldots, a_m\}$ is the set of algorithms (sorting, searching, trees, graphs)
- D is the input dataset or user-provided values
- V is the visualization engine
- E *is* the execution trace of an algorithm
- Q *is* the assessment module
- F is the learner feedback and performance metrics

Each algorithm $a_i \in A$can be modeled as a sequence of deterministic execution steps:

$$a_i = \{s_1, s_2, \ldots, s_k\}$$

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where each step s_j transforms the data state:

$$D_{j+1} = f(s_j, D_j)$$

The visualization engine V translates each execution state into a graphical representation:

$$V(D_j) \rightarrow G_j$$

where G_j is the graphical representation of the visual state at step j.

The Large Language Model (LLM) produces explanations for execution traces:

$$L(E_j, C_u) \rightarrow X_j$$

where:

- E_j is the current execution step
- C_u represents the user's comprehension level (easy, moderate, hard)
- X_j is the produced natural language explanation

To validate the explanations, the validation process is done by matching X_j with the deterministic execution E_j:

$$Valid(X_j) = \begin{cases} 1, & \text{if } X_j \in E_j \\ 0, & \text{otherwise} \end{cases}$$

The assessment module produces trace-based questions:

$$Q_j = g(E_j, X_j)$$

User performance feedback is computed as:

$$F_u = \frac{\sum Correct\_Responses}{Total\_Questions}$$

B. Performance Evaluation Of Tracking Modalities

Performance evaluation is concerned with assessing the efficacy of various tracking modalities employed for analysing learner engagement and system response. The assessment takes into account three major modalities: visual tracking, interaction tracking, and learning performance tracking.

1. Visual Tracking Accuracy

Visual tracking is concerned with ensuring that visualization states accurately reflect the execution of the algorithm. Accuracy is calculated as follows:

$$Accuracy_v = \frac{Correct\_Visual\_States}{Total\_Execution\_Steps}$$

This measure helps to ensure that every frame of animation perfectly maps to the algorithm trace.

2. Interaction Tracking Efficiency

Interaction tracking refers to the system's responsiveness to user interactions like step control, input change, and difficulty choice. It is calculated as:

$$Efficiency_i = \frac{Successful\_Interactions}{Total\_User\_Actions}$$

Lesser latency and greater interaction success rate imply a better system usability.

3. Learning Performance Tracking

Learning performance is tracked by pre-test and post-test scores to quantify knowledge gain:

Learning_Gain=PostTest_Score-PreTest_Score

Further, accuracy of quiz answers corresponding to visualization steps is calculated as:

$$Accuracy_q = \frac{Correct\_Answers}{Total\_Questions}$$

4. Explanation Consistency Metric

For assessing the reliability of LLM, explanation consistency is calculated by checking the validity of explanations against execution traces:

$$Consistency = \frac{Validated\_Explanations}{Total\_Generated\_Explanations}$$

5. Overall System Performance Index

An overall performance index is calculated as:

$$P_{overall} = w_1 Accuracy_v + w_2 Efficiency_i + w_3 Accuracy_q + w_4 Consistency$$

where w_1, w_2, w_3, w_4 are weighted coefficients reflecting system priorities.

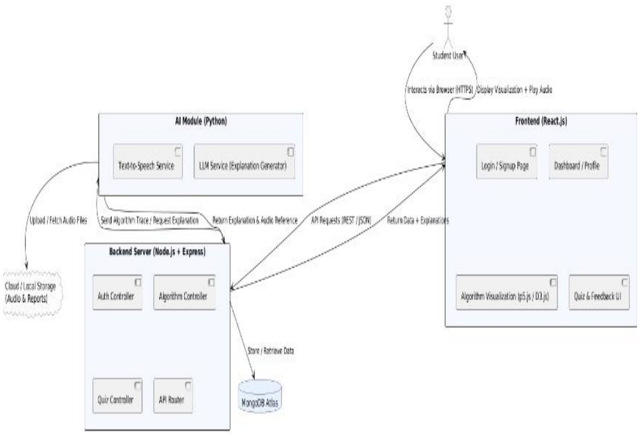
C. System Architecture

The proposed system, AlgoVista, introduces an AI-enhanced algorithm visualization system with a tool that is built using the MERN stack and Python-based LLM integration.

• Frontend: React.js for interaction and visualization using D3.js or p5.js.
• Backend: Node.js and Express.js for API routing and database operations.
• Database: MongoDB Atlas for storing user, algorithm trace, and feedback data.
• AI Layer: Python-based LLM and Text-to-Speech modules for explanation and audio narration.

The system will support the following functionalities:

1. Mode Selection: Easy, Moderate, or Hard modes for varying explanation complexity.
2. Dynamic Visualization: Real-time visualization of algorithm traces.
3. LLM-Generated Explanations: Contextual and language-flexible explanations.
4. Quiz and Feedback: Trace-based question generation and adaptive feedback.



Dig-1 System Architecture

IV. RESULTS

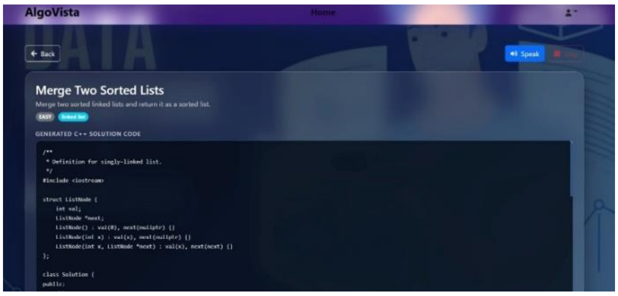
The AI powered Data Structure and Algorithm visualization tool that is in the plan, is expected to greatly enhance students' understanding and motivation through adaptive, interactive, and multimodal learning methods.

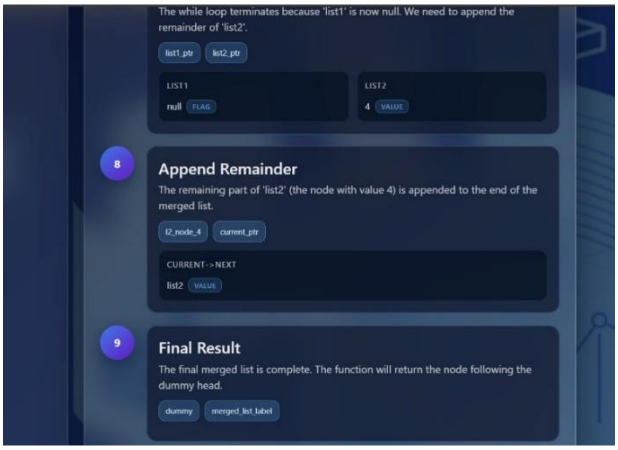
The platform will aptly illustrate algorithm functioning by step, wise animated execution that corresponds accurately to deterministic trace execution of different algorithms such as sorting, searching, and tree operations. In every visualization state, there will be an AI, generated explanation thus, students will understand both the operational flow and the underlying logic of the algorithm. As a result of adding levels of difficulty that are tailored to the learner's needs, explanations will be made to match the learners' understanding level dynamically.

The Large Language Model component will produce natural language long, form, detailed explanations that are aligned with the execution of the algorithm steps. These explanations will then be verified with the execution traces, which will decrease errors and make the explanations more reliable. Furthermore, the text, to, speech module will provide audio narration that is synchronized with the visuals, thus facilitating auditory learners and making the material more accessible.

The platform will be very responsive when you are utilizing it. You will notice the changes a few moments after you do something on the platform. This is due to the fact that the platform is capable of performing what you do and showing you things at the same time very quickly. Besides, the platform is able to follow your activities. Accordingly, the platform can present you with the content at the right moment. These components include the visually part, the one that uses intelligence for explanations and the one that assesses your performance.

User will continuously experience a good platform performance. Moreover, the system will be designed to accommodate the concepts of scalability and extensibility, thus making it possible to integrate new algorithms, data structures, and cutting, edge learning analytics in later versions. The project will be a dependable and smart educational assistant for students, teachers, and independent learners in the end, thus, helping to raise the level of achievement in learning Data Structures and Algorithms.





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V. CONCLUSION AND FUTURE WORK

In this paper, we have shown the potential of an AI-based Data Structures and Algorithms (DSA) visualization system to improve conceptual understanding through adaptive and interactive learning. The key takeaway of this paper is the integration of deterministic algorithm execution, dynamic visualization, Large Language Model-based explanations, and simultaneous assessment in a single platform. The proposed system has the capability to convert passive algorithm explanations to active ones using animations, natural language, and audio explanations.

The proposed system has the capability to address the shortcomings of conventional DSA learning and existing visualization systems by providing personalized explanations, real-time feedback, and continuous assessment of learners. The system is designed to be scalable and extensible, and new algorithms and learning modules can be easily added to the system. Future work will focus on expanding the list of algorithms, improving explanation validation for LLM-based content, and incorporating advanced learning analytics and adaptive testing.

REFERENCES

[1] S. Halim, "Visualgo–visualising data structures and algorithms through animation". Olympiads in informatics, 2015, https://ioi.te.lv/oi/files/volume9.pdf#page=245
[2] L. Yan, R. Martinez-Maldonado and D. Gašević, "Generative Artificial Intelligence in Learning Analytics: Contextualising Opportunities and Challenges through the Learning Analytics Cycle", November 2023, https://arxiv.org/pdf/2312.00087
[3] E. Kasneci, K. Seßler, S. Küchemann and M. Bannert, "ChatGPT for good? On opportunities and challenges of large language models for education", Learning and individual …, January 2023, https://www.sciencedirect.com/science/article/pii/S1041608023000195
[4] W. Shang and X. Huang, "A survey of large language models on generative graph analytics: Query, learning, and applications", IEEE Transactions on Knowledge and, January 2025, https://ieeexplore.ieee.org/abstract/document/11192225/

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 02 , February - 2026

[5] A. Bewersdorff et al, "Taking the Next Step with Generative Artificial Intelligence: The Transformative Role of Multimodal Large Language Models in Science Education", January 2024, https://arxiv.org/pdf/2401.00832
[6] M. Paredes-Velasco, J. Velázquez-Iturbide and M. Gómez-Ríos, "Augmented reality with algorithm animation and their effect on students' emotions", January 2023, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9449290/
[7] I. Makohon, "Development of Visualization-Animation Software for Learning Transportation Algorithms", January 2016, https://core.ac.uk/download/217293874.pdf
[8] S. Simonák, "Algorithm visualization using the vizalgo platform", Acta Electrotechnica et Informatica, January 2013, https://search.proquest.com/openview/ab939e7b45235e97466150541ec49300/1?pq-origsite=gscholar&cbl=2016346
[9] A. Aristovnik, D. Keržič, D. Ravšelj, N. Tomaževič and L. Umek, "Impacts of the COVID-19 pandemic on life of higher education students: A global perspective". Sustainability, 2020, https://www.mdpi.com/2071-1050/12/20/8438?kuid=51e26176-e675-46e7-ab1d-87620d9ab0df&kref=https%3A%2F%2Fshemaps.com%2Fblog%2Fgis-careers-social-media%2F
[10] J. L. Moore, C. Dickson-Deane and K. Galyen, "E-Learning, online learning, and distance learning environments: Are they the same?", The Internet and higher education, January 2011, https://www.sciencedirect.com/science/article/pii/S1096751610000886
[11] G. Deeva, J. Smedt, C. Saint-Pierre, R. Weber and J. Weerdt, "Predicting student performance using sequence classification with time-based windows", December 2022, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9359516/
[12] J. L. Moore, C. Dickson-Deane and K. Galyen, "E-Learning, online learning, and distance learning environments: Are they the same?", The Internet and higher education, January 2011, https://www.sciencedirect.com/science/article/pii/S1096751610000886
[13] M. Imran and N. Almusharraf, "Google Gemini as a next generation AI educational tool: a review of emerging educational technology", Smart Learning Environments, January 2024, https://link.springer.com/article/10.1186/s40561-024-00310-z
[14] J. Lin and H. Zhang, "Data structure visualization on the web", 2020 IEEE International Conference on Big, January 2020, https://ieeexplore.ieee.org/abstract/document/9378249/
[15] P. Brusilovsky and E. Millán, "User models for adaptive hypermedia and adaptive educational systems", The adaptive web: methods and strategies of web, January 2007, https://link.springer.com/content/pdf/10.1007/978-3-540-72079-9_1?pdf=chapter%20toc
[16] L. L. M. Team, A. Modi, A. S. Veerubhotla and A. Rysbek, "Evaluating Gemini in an arena for learning", arXiv preprint arXiv …, January 2025, https://arxiv.org/abs/2505.24477
[17] M. Mladenović and Ž. Žanko, "The impact of using program visualization techniques on learning basic programming concepts at the K–12 level", Computer Applications in …, January 2021, https://onlinelibrary.wiley.com/doi/abs/10.1002/cae.22315
[18] C. Chiu, "Verification of Theory Based Design Features for Designing Online Instruction for Students with Learning Disabilities and Other Struggling Learners", January 2013, https://core.ac.uk/download/213401232.pdf
[19] F. Vateha and S. Šimoňák, "Comparative Visualisation of Algorithms and Data Structures", Computing and Informatics, January 2025, https://www.cai.sk/ojs/index.php/cai/article/view/6953
[20] J. Kuljis and L. Baldwin, "Visualisation Techniques for Learning and Teaching Programming", January 2000, https://core.ac.uk/download/14416787.pdf
[21] J. Lin and H. Zhang, "Data structure visualization on the web", 2020 IEEE International Conference on Big, January 2020, https://ieeexplore.ieee.org/abstract/document/9378249/