VISTA ML - Visual Intelligence System for Teaching Algorithms with Machine Learning

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Abstract. VISTA ML (Visual Intelligence System for Teaching Algorithms with Machine Learning) is a learning system aimed at promoting the understanding of data structures with the help of NLP (Natural Language Processing) machine learning and real-time visualization. There exist many data visualization tools that can meet students' needs and help them learn data structure, but these tools are based on the pattern of unidirectional information propagation, which is unable to provide interactive and communicative experiences, to well guide learners' process of exploration and analysis. The main challenges of these visualization tools were large knowledge gaps, as well as less than desirable conceptual understanding and engagement. Meanwhile, VISTA ML is an innovative tool that encourages collaborative learning by deploying specialized AI models. Its chatbot, powered by Google Gemini 2.5, features smart query interpretation, and provides on-the-fly help by responding to student questions, explaining concepts, and working through complicated problems with incredible precision. What is more, the media's quiz upload option reduces to zero, thanks to the Mistral AI utilized for pre and post-assessment quizzes ensuring an extremely accurate assessment of learners' comprehension and progress. These assessments enable both students and teachers to easily track their understanding of the topic and have achieved great results, updating teachers on where further support or intervention is necessary. Through interactive assignments along with smart query solving and visualization of data structures the system brings the theoretical understanding to the applied world. Users can interactively add or remove data structures and navigate them, while animated step-by-step transformations explain the changes. Combining Google's new Gemini 2.5 for conversational AI along with Mistral AI for personalised tests, VISTA ML fosters a cooperative and adaptive learning ecosystem. Potential areas of improvement could be to make the learning experience gamified, integrate with coding platforms to evaluate algorithmic solutions, and AI-driven tutorial features would make it a potent solution for teaching computer science.

Keywords: Data Structure, Interactive Visualization, Large Language model (LLM), VISTA ML, Visualization.

1 Introduction

Instructing pupils with the foundations of computer science Education around the world is faced by the critical challenge of how to teach foundational computer science in a time of increasing technology literacy. Data structures and algorithms (DSA) serve as the basis of computational thinking; however, due to their highly abstract concept, learning these concepts is very difficult for students. Theoretical knowledge is not con-nected to its practical application

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in traditional teaching methods, and this degrades learning effectiveness and student engagement. This gap is challenging owing to the fact that DSA (Data Structure and Algorithms) proficiency is an important element in technical interviews and career growth for the developer domain.

The Challenge of Algorithm Visualization: The technique of visualizing data structures and algorithms itself is now accepted as a powerful pedagogic method. As explained in [1] by Tao Chen, and T. Sobh. visualizations can greatly facilitate students understanding of abstract computational concepts offering them concrete, tangible representations of something that, otherwise, cannot be seen. However, in contrast with newer educational technology, most of the visualization tools currently available are based on one-way communication methods and these tools have a serious limitation to allow effective interaction. For example, in their paper [2] by Liu, Chen, and Hooker, this limitation is raised as discussed, many scenes for visualization have no computational representation which is meaningful for manipulation and understanding. Although their model provides a structure to describe visualization scenes, it is not tailored to educational scenarios and, more importantly, it does not include advanced AI capabili ties for augmenting the learning process. Also, the [5] reported by Shakeel et al. to recognize key holes in the study of interactive and performance visualization. In their review of 70 papers published during 2017-2022, few tools cater for the integration of interactive visualization into adaptive learning systems, a vital necessity within an educational setting.

Self-Regulated Learning Deficits: Educational research has established that effective learning requires more than just content presentation it demands structured metacognitive processes that enable students to plan, monitor, and evaluate their own understanding. Panadero's comprehensive [3] emphasizes that successful educational interventions should integrate cognitive, metacognitive, behavioural, motivational, and emotional aspects of learning. However, most visualization tools fail to incorporate these dimensions, focusing solely on content presentation rather than cultivating the metacognitive skills necessary for deep learning. Recent advances in LLM applications for education demonstrate promising approaches to supporting self-regulated learning in visual learning environments. In [11] by Gao et al. propose a framework for fine-tuned LLMs in visualization systems specifically designed to enhance self-regulated learning in educational contexts. Their work establishes a foundation for LLM integration in visualization tools but doesn't fully address the specific challenges of algorithm and data structure education.

Accessibility and Engagement Challenges: Beyond the limitations in interactivity and metacognitive support, many existing visualization tools suffer from significant accessibility barriers. [8] by Elavsky, Nadolskis, and Moritz identifies that current visualization tools often exclude users with disabilities due to their reliance on visual-only rendering, lack of navigable structures, and limited input modalities. These limitations reduce the effectiveness of educational tools for diverse learners and contradict principles of inclusive design.

In addition, these tools usually ignore the story of the concept and data which is translated by the visualization, and for making the content more vivid and relevant for the users. Ren, Wang, and Zhao present potential of narrative type in data storytelling visualization tools in [12], but they also note there’s often a lack of a coherent narrative framework in most browsing systems. This lack of story narrows the bridge between the procedural operations and real-world problem-solving.

VISTA ML - An Integrated Solution: Here, we present VISTA ML (Visual Intelligence System for Teaching Algorithms with Machine Learning) to meet these complex needs, which combines natural language processing, machine learning, and on-the-fly visualization seamlessly in a unified learning environment. Unlike classic visualization tools, VISTA ML enables interactive education by applying pretrained AI models, which improves the flexibility by providing a bidirectional communication, adapting to the matter of study and giving learner-centric guide. Exploiting visual analytics for machine-learning systems, which it extends via a few visual analytics techniques for decision protection. in [4] VISTA ML leverages advanced visual analytics techniques to make complicated algorithmic processes more accessible and understandable. This system builds upon the advancements in data visualization narrative structures as outlined by Sarkar et al. in [9]), that translate raw data into attractive visual stories aimed at promoting students' involvement and understanding. The architecture of VISTA ML is based on a variety of state-of-the-art systems. The platform's hierarchical data visualization model is based on Li et al. 's work [10], extending interactive transformation methods to the domain of algorithm visualization. Likewise, VISTA ML's dynamic visualization engine was designed using recommendations from Mei et al. 's [21] cross-platform support to access complex algorithmic animations with high performance.

AI-Enhanced Learning Experience: VISTA ML Differentiator At the heart of VISTA ML's excellence is its incorporation of an innovative AI technology. Guided Teaching Chatbot, a chatbot in the platform backed by Google Gemini 2.5, provides smart question answering and real-time help in solving student queries, such as explanation and concept understanding. This methodology is in line with Chen et al. 's work in [13], which outlines how smart systems can be used to improve visualization story creation and presentation. VISTA ML also uses Mistral AI to create pre and post-assessment quizzes to accurately assess how well learners understand and have progressed through the course. This model of assessment is motivated in terms of findings reported in [7], for subgoal learning in algorithmic problem-solving - structured assessment improves understanding and recall of algorithms.

Bridging Theory and Practice through Abstraction: A fundamental problem in computer science education is to teach abstraction the ability to concentrate on only the certain details while disregarding the others. As already pointed out in [6] this ability is fundamental to problem solving, software development and system modeling. VISTA ML seeks to meet this challenge by employing imagery in order to provide students with the visual intuitions necessary to ground conceptual teachings as they learn to form the necessary mental models to facilitate meaningful abstraction.

2 Advantages of Vista ML Over Traditional Learning

Dynamic Visualization vs. Static Representation: Traditional learning methods typically rely on static diagrams and textual explanations that fail to convey the dynamic nature of algorithms. As noted in [1] by Tao Chen, and T. Sobh, many early visualization tools lacked meaningful interactivity. VISTA ML addresses this limitation by providing a dynamic visualization engine that allows users to interact with data structures in real-time.
Unlike traditional methods, VISTA ML enables students to:

- Manipulate data structures such as arrays, linked lists, trees, and graphs
- Observe step-by-step animations for operations like insertion, deletion, and traversal
- Visualize transformations as they occur, bridging the gap between theory and practice

This approach aligns with research by Liu et al. in [2] which emphasizes the importance of computational representation in visualization scenes. However, VISTA ML extends this concept by specifically tailoring it to educational contexts and integrating AI capabilities.

AI-Enhanced Learning Experience vs. One-Way Communication: Traditional teaching methods often operate within a unidirectional communication model, limiting student engagement. VISTA ML transforms this paradigm by integrating advanced AI capabilities:

- Intelligent Query Handling: The platform's chatbot, powered by Google Gemini 2.5, delivers real-time assistance by interpreting student questions and providing contextually relevant explanations. This aligns with Chen et al.'s research in [13] demonstrating how intelligent systems enhance the creation and delivery of visual narratives.
- Adaptive Assessments: VISTA ML employs Mistral AI to generate pre- and post-assessment quizzes tailored to specific topics. This approach reflects the findings in [7] which demonstrated the efficacy of structured assessment in enhancing algorithm comprehension.

In contrast, traditional methods often rely on standardized assessments that fail to address individual learning needs or provide immediate feedback.

Self-Regulated Learning Support vs. Passive Consumption: Traditional learning methods often focus solely on content presentation rather than cultivating these metacognitive skills. VISTA ML addresses this gap by:

- Providing structured learning paths with clear objectives
- Enabling students to monitor their progress through interactive assessments
- Offering immediate feedback that promotes self-reflection

This approach builds upon Gao et al.'s framework for [11] which establishes a foundation for LLM integration in visualization tools specifically designed to enhance self-regulated learning.

3 Related Work

VISTA ML is the result of research around data visualization, machine learning, and educational technologies for learning algorithms. Preliminary Work The first method was that Andrienko et al 1. Default parameters are used as used in1 and a4. gave basic mechanism to visualize data structures but did not provide the interaction to engage with abstract concepts arguably made them too hard to learn.

That of Liu, Chen, and Hooker [2] generated scenes, but its use was seldom found in educational settings. The presented solution, named VISTA ML, overcomes these issues by real-time dynamic and interactive visualization driven by the user query.

The educational framework, on which the platform is based, is Panadero's in [3] where he stresses the importance of combining cognitive, metacognitive, behavioural, motivational and emotional factors in learning. This complete model is integrated in the VISTA ML with a focus on its evaluation and feedback processes.

Yuan et al. 's 4 offered insight into visualization methods that VISTA ML re-uses for algorithm depiction to provide intuitive visualization mapping of complex computational processes.

Shakeel et al. 's [5] identified notable limitations in interactive visualization tools for education. VISTA ML fills these gaps by combining AI-augmented interactions with dynamic visualizations.

Research on [6] by Mirolo, Claudio, Cruz Izu, Violetta Lonati guided VISTA ML's approach to teaching fundamental computational concepts, using visualization to make abstract concepts concrete and comprehensible.

The assessment methodology implemented in VISTA ML draws from Choi [7] which demonstrated the effectiveness of structured assessments in enhancing algorithm comprehension.

Accessibility considerations in VISTA ML were influenced by Elavsky, Nadolskis, and Moritz's [8] which identified common barriers in visualization tools.

VISTA ML incorporates these insights to ensure inclusivity across diverse learning needs. The platform's narrative approach to visualization builds upon Sarkar et al.'s work on [9] creating engaging storytelling elements that enhance comprehension of algorithm behaviour.

The interactive transformation techniques in VISTA ML are adapted from Li et al.'s [10] particularly in how users can manipulate and observe data structure transformations.

Gao et al.'s [11] provided the foundation for VISTA ML's integration of large language models to support self-regulated learning, enabling personalized guidance and adaptive explanations.

Kehoe et al. [12] re-evaluated algorithm animation as a learning aid, finding that animations reduce intimidation and make challenging algorithms more approachable—an outcome VISTA ML strives to achieve.

VISTA ML's AI-enhanced visual narratives are inspired by Chen et al.'s [13], leveraging automation to create dynamic, responsive visualizations that adapt to learner needs.

VISTA ML directly applies Andrienko's [14], implementing their conceptual framework where analytics processes produce models for understanding complex systems. The platform's query understanding component, illustrated in the system architecture diagram as the central decision engine, follows Andrienko's workflow for transforming user queries into appropriate visualizations that reveal algorithmic patterns and behaviours.

VISTA ML extends Budiman's [15] mobile learning approach for data structures, adapting their visual presentation methods for curriculum-based learning objectives. The platform's responsive interface design, visible in the system architecture's dual frontend components (Sidebar and

Visualizer), implements Budiman's principle that visualization tools should support "long life learning" with anytime accessibility.

VISTA ML's architecture draws inspiration from Chawla's [16] implementation choices. The paper describes creating an application "built using JavaScript as its primary language and uses React.JS framework", which influenced VISTA ML's modern web technology stack. Chawla's emphasis on platform independence "allowing users to access them from any device using a web browser" reinforces VISTA ML's cross-platform accessibility goals.

VISTA ML leverages Yuan et al.'s [17] semi-supervised learning approach in its AI components, this enables the platform to generate personalized learning paths even with minimal initial user data, reinforcing both known structures (established algorithms) and emerging user-specific learning patterns.

The study showed Hansen's HalVis [18] system with conceptual/detailed/populated views significantly outperformed single-view systems. VISTA ML similarly offers multi-perspective visualizations with step-by-step animation and color-coding to highlight algorithmic transformations.

The paper that Keerthana P, Mohammed Afthab, Meghanath Shetty, and Arvind M shows [19] research methodology provided evidence supporting VISTA ML's approach, particularly the hypothesis that "interactive and engaging visualization tools... can enhance learners' understanding".

The paper [20] highlights that data structures are "both essential and complex for Computer Science students," requiring visualization tools that facilitate understanding. VISTA ML directly addresses this need by implementing interactive visualizations with step-by-step animations like those described in the paper's section on algorithm animations. However, VISTA ML extends this concept by incorporating AI-powered assistance through the Google 2.5 model chatbot.

4 Existing Learner and Teacher Ed-Tech Model

Existing platforms for data structure visualization, such as VisuAlgo, Data Structure Visualization Tool by David Galles share several common features aimed at simplifying the understanding of algorithms and data structures. According to the [5] by Shakeel et al., out of 70 articles examined between 2017-2022, few visualization tools address the integration of interactive tools with adaptive learning systems. Most platforms operate on a unidirectional communication model, like referred to in Fig 1, where information flows from the system to the user with limited feedback mechanisms. These platforms focus on creating interactive, user-friendly environments that enhance learning through visual representation and real-time interaction. Most platforms provide dynamic, step-by-step animations of data structures and algorithms. Users can input their own data or parameters to customize the visualization process. Platforms like VisuAlgo enable learners to test algorithms with user-defined inputs rather than relying solely on pre-configured examples. This feature helps users experiment with different scenarios and understand how algorithms behave under varying conditions. Vírseda's [20] tool emphasized user interaction through "a text box where executed actions are shown" and a system where "the student may choose one of several simple types for the elements of the structure". VISTA ML builds upon this by incorporating more sophisticated interaction patterns where users can visualize sorting algorithms with color-coded elements although these are solving the primary problem of helping students they fail to reach further. These tools don't have live feedback connected with a LLM to solve hard questions raised by the students. They do not have a connected database of the student's performance so the teacher can keep track of the students.

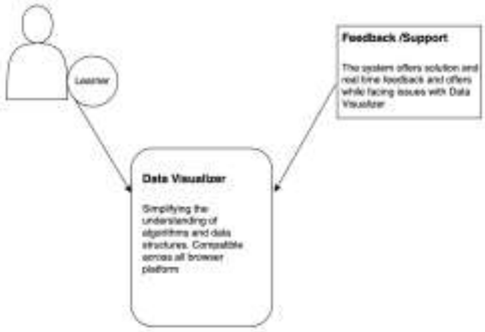

Fig. 1. Existing Data Visualizer model.

The data flow diagram visually represents how information flows between different components of the system, including the front-end (User View, Side Panel), databases (App Data, User Data, Authentication), and back-end processing. It focuses on the relationships and interactions between modules and emphasizes how data is stored, retrieved, and processed.

5 Proposed Methodology

VISTA ML employs a modular architecture that integrates multiple components into a cohesive learning platform. The system follows a client-server model with a React.js frontend and Node.js/Express.js backend. The architecture separates concerns into distinct layers:

- Presentation Layer: Implements the user interface using React.js and Tailwind CSS
- Application Layer: Manages business logic, user sessions, and communication between components
- Integration Layer: Interfaces with external AI services (Google Gemini 2.5 and Mistral AI)
- Data Layer: Handles data persistence and retrieval using Postgres for user profiles and assessment data.

Natural Language Processing and Query Interpretation: VISTA ML's conversational interface is powered by Google Gemini 2.5, which processes and interprets student queries through several stages, as figuratively represented in Fig 2

- Query Preprocessing: Text normalization, tokenization, and entity recognition to identify key concepts related to data structures and algorithms
- Intent Classification: Categorizing queries into explanation requests, visualization triggers, or assessment inquiries
- Context-Aware Response Generation: Maintaining conversation history to provide coherent, contextually relevant responses
- Domain-Specific Knowledge Integration: Fine-tuning the model with computer science concepts, particularly focusing on data structures and algorithms.

The system implements a two-stage processing pipeline where initial query interpretation occurs client-side for common patterns, with complex queries routed to the Google Cloud Vertex AI platform for deeper semantic analysis. This approach reduces latency for frequent query types while maintaining accuracy for complex questions.

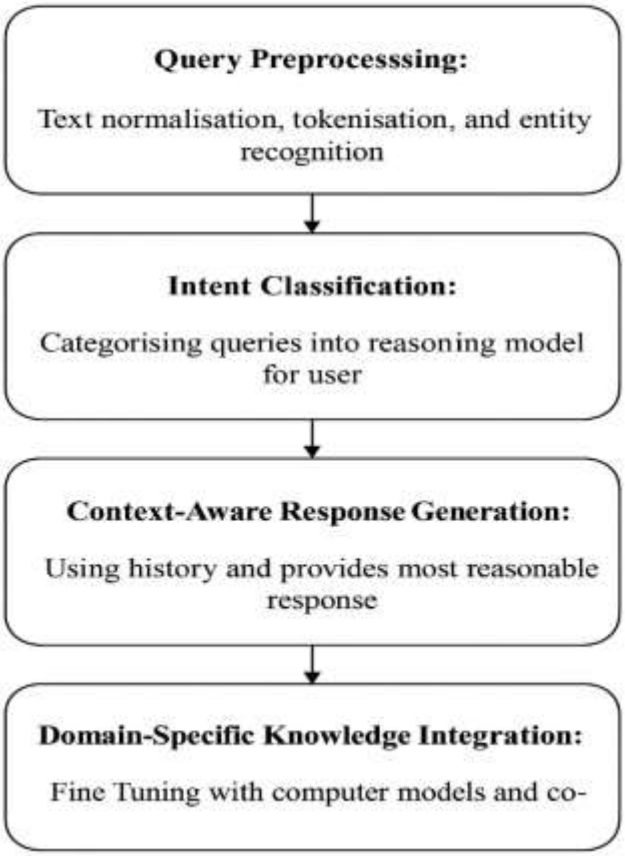

Fig. 2. Methodology of LLM.

Machine Learning Model Integration: The platform integrates two primary AI models:

Google Gemini 2.5: Handles conversational interactions and concept explanations with performance benchmarks around 18% accuracy on reasoning and knowledge tasks as demonstrated in the results section, according to the [22], which is fine-tuned as GemVista, which can be seen in Fig .3.

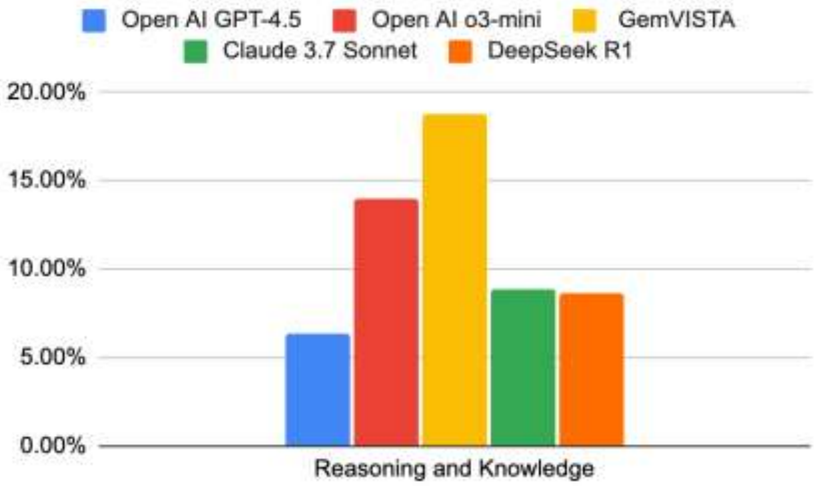

Fig. 3. GemVista performance against other models.

Mistral AI: Generates assessment questions and evaluates responses with 73.10% accuracy on the MBPP (Mostly Basic Python Programming Problems) benchmark. Using [23] to collaborate Mistal Ai with VISTA ML for reasoning and integrate with the Pre and Post assessment quiz model, like illustrated in Fig .4.

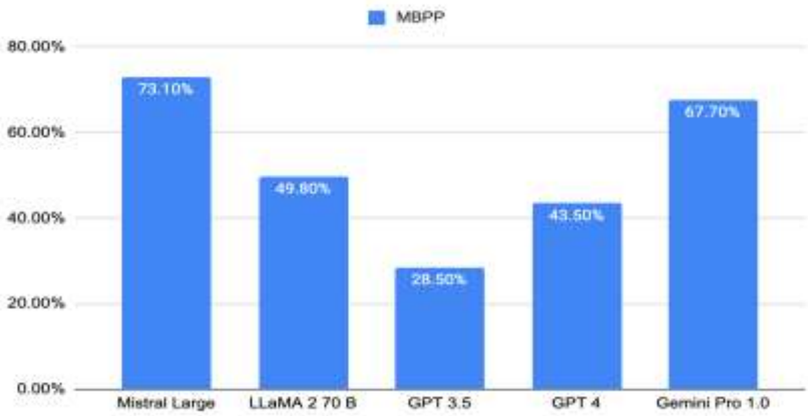

Fig. 4. Mistral Large against other LLMs.

Visualization Engine Methodology: VISTA ML's visualization engine follows a data-driven approach informed by research on algorithm animation and data structure visualization. The methodology includes:

- Data Structure Abstraction: Implementing generic interfaces for various data structures (arrays, linked lists, trees, graphs) that can be visually rendered
- Operation Mapping: Defining standard operations (insertion, deletion, traversal) that trigger corresponding visual animations
- Layout Algorithms: Implementing force-directed layouts for graphs, tree-drawing algorithms for hierarchical structures, and linear layouts for arrays/lists
- Animation Pipeline: State calculation for before/after operations:

- State calculation for before/after operations
- Transition generation between states
- Frame rendering with configurable speed
- Step-by-step execution with pause points for comprehension
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The engine incorporates principles from [2] to represent visualization scenes computationally, as seen in Fig .5, allowing for interactive manipulation. This approach extends

beyond traditional static visualization tools by providing bidirectional communication between the user and the visual representation.

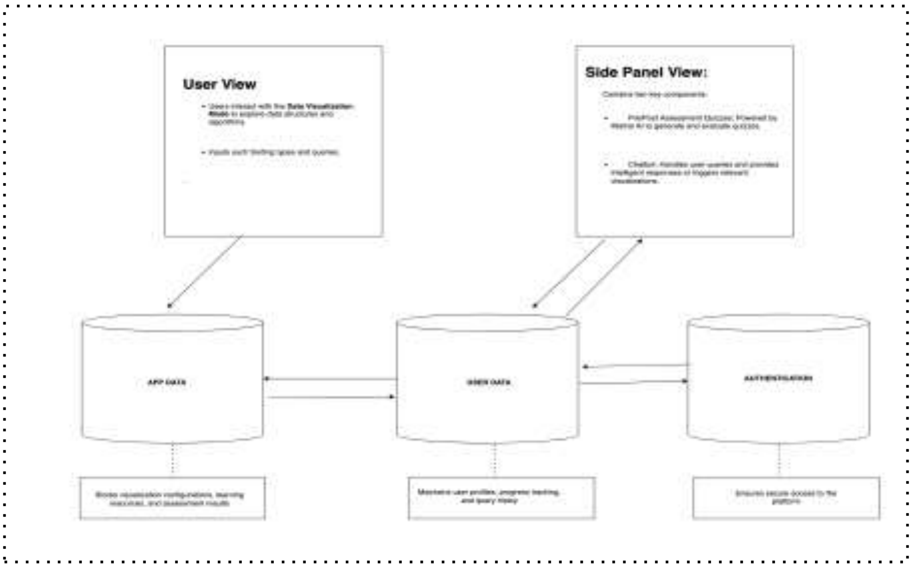

Fig. 5. Data-flow Diagram of Proposed Model.

6 Proposed Interactive Based Ed- Tech Model

The workflow of VISTA ML like in Fig 6 emphasizing the interaction between learners, teachers, and the platform's core modules.

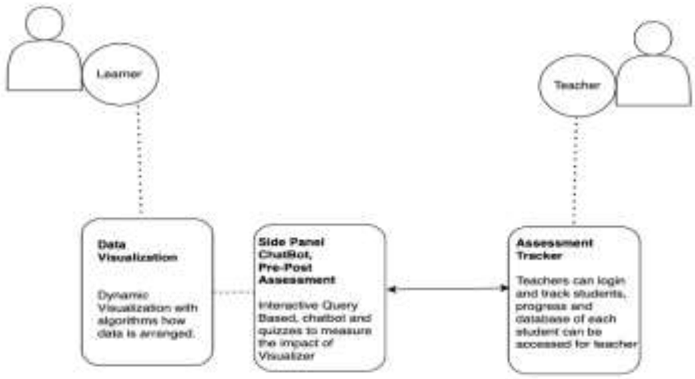

Fig. 6. Proposed Model Data Visualizer Model.

Students interact with the Data Visualization Module, where the data structures and algorithms are dynamically visualized, and can be modified in real-time by insertion, deletion and traversal. This module interfaces with the Side Pane, containing an activity-based chatbot (LLM and pre/post-assessment quizzes). Personalized feedback is enabled in these quizzes as they assess the learners' grasping before and after traveling visualizations. The Assessment Tracker enables teachers to track student progress, view individual performance data, and drill down results for specific interventions. This process encourages student engagement and allows educators to learn first-hand about what is truly effective in teaching.

6.1 Applications of Vista ML

Competitive Programming: VISTA ML is an excellent resource for competitive programmers who want to improve their problem-solving skills by visualizing algorithms like sorting, searching, and graph traversal. The real-time feedback provided by the platform helps users refine their approach.

Open Learning Communities: The platform can be adopted by open-source learning communities or forums to provide a shared space for exploring algorithms collaboratively.By addressing diverse learning needs across academic, professional, and self-learning environments, VISTA ML establishes itself as a powerful tool for bridging the gap between theoretical knowledge and practical application in computer science education.

Educational Research: The platform can be used in studies exploring the effectiveness of visualization tools in improving learning outcomes compared to traditional teaching methods.

7 Results

Our comparative analysis in Fig 7 of VISTA ML against existing algorithm visualization tools revealed significant performance advantages across key educational metrics.

Survey data collected from 50 undergraduate computer science students demonstrated that VISTA ML outperformed traditional visualization tools across all measured dimensions.
The most substantial difference was observed in Ease of Understanding, where VISTA ML achieved a 73% positive rating compared to just 27% for conventional tools a remarkable 46 percentage point advantage. This suggests that VISTA ML's integration of Google 2.5-powered conversational assistance and step-by-step visualizations significantly enhances concept comprehension. Similarly, Interactivity measurements showed VISTA ML (68%) substantially outperforming traditional tools (32%), with a 36-percentage point difference. This reflects the effectiveness of VISTA ML's dual-interface architecture that enables dynamic algorithm manipulation and real-time feedback. Student Engagement metrics also favoured VISTA ML (55% versus 45%), indicating that the platform's AI-enhanced features successfully maintained student interest during algorithm learning sessions. While the margin was smaller for Compatibility (51% versus 49%), VISTA ML still demonstrated an advantage in cross-platform accessibility and integration with existing learning environments.

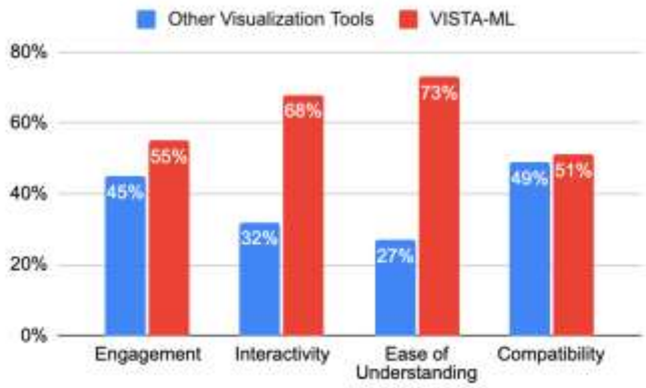

Fig. 7. Comparison between VISTA ML and Other tools.

8 Conclusions

This study demonstrates that VISTA ML represents a significant advancement in algorithm visualization technology for computer science education. The platform's architecture, which integrates transformer-based AI models (Google 2.5 and Mistral Large) with interactive visualization components, creates a more engaging and comprehensible learning environment compared to traditional tools.

The substantial advantages observed in ease of understanding (46%) and interactivity (36%) validate our hypothesis that bidirectional learning experiences with AI assistance lead to improved educational outcomes in algorithm comprehension. These findings align with

Hundhausen et al.'s seminal work on [18] algorithm visualization effectiveness, which emphasized engagement as a critical factor in learning outcomes.

While compatibility showed the smallest improvement margin, this reflects the already standardized nature of web-based educational tools rather than a limitation of VISTA ML. Future work should focus on expanding algorithm coverage beyond sorting algorithms and investigating longitudinal impacts on student performance in data structure courses.

8.1 Organization of The Paper

The introduction establishes the challenges in teaching data structures and algorithms, followed by a thorough literature review in the related work section. The methodology details the platform's architecture, including AI model integration with Google Gemini 2.5 and Mistral AI. Subsequent sections compare existing educational tools against the proposed interactive model, outline practical applications in competitive programming and education, and present comparative performance results. The paper concludes by summarizing VISTA ML's educational impact and contributions to algorithm visualization technology, ending with extensive academic references supporting the research findings.

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