ML-Quest: a game for introducing machine learning concepts to K-12 students

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ABSTRACT
Owing to the predominant role of Machine Learning (ML) across domains, it is being introduced at multiple levels of education, including K-12. Researchers have leveraged games, augmented reality and other ways to make learning ML concepts interesting. However, most of the existing games to teach ML concepts either focus on use-cases and applications of ML instead of core concepts or directly introduce ML terminologies, which might be overwhelming to school students. Hence, in this paper, we propose ML-Quest, a game to incrementally present a conceptual overview of three ML concepts: Supervised Learning, Gradient Descent and K-Nearest Neighbor (KNN) Classification. The game has been evaluated through a controlled experiment, for its usefulness and player experience using the TAM model, with 41 higher-secondary school students. Results show that students in the experimental group perform better in the test than students in the control group, with 5% of students in the experimental group scoring full marks. However, none of the students in the control group could score full marks. The survey results indicate that around 77% of the participants who played the game either agree or strongly agree that ML-Quest has made their learning interactive and is helpful in introducing them to ML concepts.

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1. Introduction

Machine Learning (ML) is pervasive today owing to the drastic increase in the availability of data and computational power (Janiesch et al., 2021) and spawns across domains (Kahn & Winters, 2021; Lund & Ng, 2018; Nassif et al., 2019; von Lilienfeld, 2020). Considering the vast presence of ML and its impact on society, it has become important for students to be prepared for the upcoming digital era and empower themselves as digital citizens (McClelland & Grata, 2018). Uncovering the basic concepts of ML at an early stage could help students improve their cognitive thinking and could also prepare them for pursuing higher education and future career in ML (Hitron et al., 2019; von Lilienfeld, 2020). Nevertheless, it should be noted that students should not be overwhelmed because of the complexity of an unknown concept (Hitron et al., 2019; Mariescu-Istodor & Jormanainen, 2019). Therefore, there is a need to introduce ML concepts at an early stage without burdening them with inner complex details.

Overtime, many studies have shown the effectiveness of games to teach multiple concepts across different domains such as debugging (Arnab et al., 2015; Venigalla & Chimalakonda, 2020), computer
architecture (Tlili et al., 2016) and social awareness (Venigalla et al., 2020). Games have been considered to be entertaining and engaging (Sung & Hwang, 2018). Teaching concepts through games could help learners perceive learning as fun without being overwhelmed with inner details of the concepts (Eagle & Barnes, 2009; Krajcsi et al., 2019).

There have been attempts to introduce ML concepts such as training and testing of the models through games (Giannakos et al., 2020). However, they do not focus on any core ML concepts such as Supervised Learning, Unsupervised Learning and so on, instead, their main focus is to make player aware of the societal impact and use-cases and applications of ML. ArtBot (Voulgari et al., 2021) is a 2D game which tries to introduce core ML concepts such as Supervised Learning and Reinforcement Learning to primary and secondary school students. However, ArtBot focuses on introducing multiple ML terminologies without providing much explanation which might be overwhelming for students. Instead teaching ML concepts scaffolded through games in an incremental fashion might be more helpful for students to learn the concepts.

To this end, we propose a 3D video game, ML-Quest which aims at introducing the definition and the working, which we call conceptual overview, of three ML concepts: Supervised Learning, Gradient Descent and KNN Classification to higher-secondary school students in a step by step manner. The game introduces ML concepts to K-12 school students with no prior knowledge of ML, without overwhelming them with inner details such as underlying complex mathematics. The key idea is to support the player to make progress in the game with clues, an instruction board, and dialogue messages to solve tasks intuitively aligned to a particular ML concept. However, the underlying ML concept and terminology is unveiled and explained at the end rather than at the beginning. Our experimental and control group based study with 41 high-school students on the parameters of Ease of Use, Usefulness, Intention to use, and Correctness are promising, with more than 70% of the participants finding the game to be interesting, interactive and useful.

The paper is structured as follows. Section 2 discusses the design methodology along with the learning outcomes of each level of ML-Quest. Sections 3 and 4 talk about the development and the user scenario of the game respectively. Sections 5 and 6 present the evaluation methodology and result of the quantitative user survey respectively. In Section 7, we discuss the game design, challenges faced while implementing the game and game limitations, which has been followed by the Section 8, where we talk about the related work. Finally, in Section 9, we conclude the paper and discuss its scope of it in the future.

2. Design methodology

ML-Quest is a 3D Role Player Game (RPG) with a quest theme. The game has been designed keeping in mind the integration of educational topics to game play through challenging tasks aligned with the concept being taught, clear instructions and giving immediate feedback to the player. The game has a storyline where the protagonist is on a mission to protect her kingdom from the enemy referred to as “red men”. The current prototype version of the game has three levels capturing three different ML concepts namely Supervised Learning, Gradient Descent and KNN Classification through well-designed tasks. At each level, the tasks have been designed by aligning to a particular ML concept and can be solved by carefully following the provided instructions (for details, refer to Section 2.1). Each level is equipped with instruction boards and dialogue boxes to guide the player. In order to create a mental model of the underlying concepts, at the end of each level, the definition and working of the ML concept is displayed and mapped with the tasks performed in the level.

Various games in the literature such as G4D (Venigalla & Chimalakonda, 2020) and Game for Computer Architecture (Tlili et al., 2016) have used different game design patterns such as Scaffolding (Gonulal & Loewen, 2018) and Early Bird (Kelle et al., 2011) to systematically address the recurring design problem and for effective game design. Scaffolding is observed to be positively bracing game development, which is evident with its wide usage in various educational games (Jantan & Aljunid, 2012; Venigalla & Chimalakonda, 2020). Hence, we have also opted for the scaffolding
technique for ML-Quest. Scaffolding in this context refers to hiding the high-level information and gradually uncovering the domain-specific concepts (Gonul & Loewen, 2018). We have implemented this idea by using metaphors for the tasks and processes at each level and unmasked these abstractions at the end of the level by defining and mapping them to the underlying ML concept.

According to Jantan et al., scaffolding consists of 10 characteristics that lead to an effective game design (Jantan & Aljunid, 2012). In our game, we have tried to capture five of these characteristics: Provides clear direction, Clarifies purpose, Keep students on task, Appropriateness of the instruction level and Continuity. The player is equipped with instructions and dialogues describing tasks and steps to complete each level. Thus, incorporating the scaffolding characteristics of Provides clear direction and Clarify purpose. The player performs tasks based on the instructions provided, which on completion is mapped to the underlying ML concept for a better understanding of the player, thus implementing the scaffolding characteristics of Keep students on task and Appropriateness of the instruction level. The game’s complexity increases gradually based on the previously performed task, and the storyline progresses with a smooth transition between the levels, implementing the scaffolding characteristic of Continuity.

2.1. Game levels and their outcomes

The current version of the game has three levels, each introducing one ML concept namely Supervised Learning, Gradient Descent and K-Nearest Neighbor (KNN) Classification respectively. In the broad scope of ML we have focused on the concepts that are fundamental and amenable (Ayodele, 2010) and hence the prototype version primarily focused on these three concepts. The concepts and learning outcomes for each level have been discussed further.

Supervised Learning: Level 1 of the ML-Quest is designed to introduce the definition and working of Supervised Learning. Supervised Learning is a well-known ML technique in which the ML model is trained to find the solution based on previous problem-solution pair (Mohamed, 2017). This level simulates a similar scenario through a maze problem. Here, the player is considered as a model. With the help of provided instructions, player needs to reach the entrance of the maze (i.e. training the model) and then solve the maze by following the same previous directions (i.e. apply the previous knowledge to solve the new problem), as shown in Figure 2. An alert message pops up in case the player does not remember the previous instructions and tries to solve the maze by hit and trial. In this way, we make sure that the player is following previously taught instructions. Once a player achieves the goal, the learning outcome is displayed which states the definition of Supervised Learning and then maps the steps involved in Supervised learning to the task performed so that the player gets a conceptual overview.

Gradient Descent: Gradient Descent is an optimization technique used to minimize a function by iterating in the direction of maximum slope and consequently reach the local minima (Ruder, 2016). In Level 2, the player is instructed to apply the steps involved in the working of Gradient Descent to solve the maze and reach the bottom-most point. The slope is used as a hint to choose the correct path (i.e. a path with maximum slope) and reach the optimum point as shown in Figure 3. After the player reaches the destination by choosing a path with maximum slope and overcoming all hurdles, the definition and working of the Gradient Descent is introduced for the player to mentally map the concept.

KNN Classification: KNN Classification is an ML technique used to classify objects based on vote of the majority elements among its k nearest neighbors (Mohamed, 2017). As the game is meant to provide an abstraction of the concept to the students, we have considered presenting this concept of majority in the form of persuasion power and voting. In Level 3, a player has two votes, and enemies have one vote each. Considering, k as three, if the player reaches the target before the two enemies, then in the three closest neighbors of the target, the player will have a majority vote (i.e. two). So, the target will be classified on the player’s side. Alternatively, if two enemies reach before, they will be in the majority and will transform the target to their side. A distance meter is provided, which shows the distance between player and target along with an enemy
meter, which shows the distance between the enemy and the target. At the end of this level, the definition and working of KNN classification mapped to the task performed in this level is displayed as shown in Figure 4.

3. Development

The game has been implemented using the Unity 3D game engine. Figure 1 depicts the step-by-step approach used for developing the game. We have used Unity assets to implement different game objects in each level along with the environment. Unity-chan asset is used for the main character, LowPoly Environment pack, house pack, AurynSky, Boxophobic and EasyPopulation-Core have been used to implement the surrounding and population. FelineGargoyle, Free medieval weapons, TextMesh pro along with different texture materials have been used to create different components of the game.

We have created a minimap at each level for the user to get the top view of the surroundings using the Unity texture rendering technique. Minimap also keeps track of the player position by dealing with the player position vectors and time variables. Player movement is controlled through input from the keyboard. The player is equipped with rich UI features such as free-roaming environment, NPCs (Non-Playable Character), and dialogue boxes, which have been implemented considering the physics-oriented events and have been controlled with the help of object listeners and events of the game objects.

The game has navigation tools such as a distance meter, path indicators, and instruction board to understand the gaming world better and reach the goal based on these perceptions. At the end of each level, the learning outcomes are displayed, attached with an object listener, to transition to the next level. The prototype of the game has been built in WebGL format and deployed on a website named Simmer.io, which is an online platform for sharing games.

4. User scenario

Consider Drishti, a school kid, enthusiastic to learn about ML related concepts and decides to play the ML-Quest. She chooses Devi as her playable character and starts the game. After reading the instructions and storyline, she clicks Next and level 1 begins. Here, Devi is in an isolated desert as shown in

![Figure 1. Architecture of ML-Quest.](image)
Devi needs to follow the red path marked in the mini-map in order to reach the destination along the way. She needs to note down the direction of her movements being displayed on the instruction board. After following the instruction set, she reaches the entrance of the maze as shown in Figure 2(a(A)). Now, Devi follows the previously noted direction of her movement to solve the maze and reach the magical door as shown in Figure 2(c(G)). While crossing the maze, if Devi steps into a wrong path, she is prompted with a warning as shown in Figure 2(b(F)) and the level restarts. As soon as she reaches the target by following all instructions and performing tasks carefully, a prompt appears with the learning outcome of level 1 and displays the definition of Supervised Learning and how she has used the steps involved in the working of Supervised Learning without even knowing it, in order to achieve the goal as shown in Figure 2(d(H)). Clicking on Next as shown in Figure 2(d(I)) takes Devi to level 2.

Devi encounters a similar maze as shown in Figure 3(a). She needs to solve the maze by choosing the path with maximum slope value, as shown in Figure 3(b(F)). To make the game more challenging, a few enemies (i.e. red men) randomly walk within the maze. Interaction with red men will reduce the health of the protagonist. If Devi passes close to an enemy, her health decreases. In the worst case, if health becomes zero, the game ends and the level restarts. Once Devi reaches the second magical door as shown in Figure 2(c) by carefully choosing the path with maximum slope, the learning outcome is displayed as shown in Figure 3(d(H)) which maps the level to steps involved in Gradient Descent concept. Clicking on Next as shown in Figure 3(d(I)) will take her to the final level.

Devi finally reaches the town of Bobs as shown in Figure 4(a). She needs to rescue three Bobs, one at a time, by getting his heart before the red men. If two red men, as shown in Figure 4(c(J)) reach before the player, Bob will take the side of red men as shown in Figure 4(c) and the level restarts. Bob can be identified by a tag hovering over the character as shown in Figure 4(b(H)). Devi starts searching for Bob with the help of distance meter, shown in Figure 4(a(F)), which displays the distance between the active Bob and Devi. If Devi finds Bob before the two red men, a dialogue appears, which tells about the next task as shown in Figure 4(b(G)). After the conversation ends, Devi collects the heart similar to the one shown in Figure 4(c(K)) and Bob comes to Devi’s side and she continues to search for the next Bob. Once all the three Bobs are rescued, a prompt, as shown in Figure 4(d(L)) appears, indicating the learning outcomes which define KNN Classification and how the steps involved in the working of this concept have been implemented through the tasks performed by Devi in this level.

Figure 2. Scenes from Level 1. Solving the Maze based on previously provided directions. (A) is minimap to see and follow red path, (B) shows instruction to follow, (C) is the player, (D) is diamond which needs to be collected to earn points, (E) tells the score, (F) warning message saying wrong path, (G) the destination (i.e magical door to next level), (H) displays learning outcome, (I) is the button to go to the next level.
5. Evaluation

ML-Quest is a 3D quest theme based game, meant to introduce ML concepts to students through interesting storyline and engaging tasks. Considering these points, ML-Quest has been primarily evaluated for its Ease of use, Usefulness and Intention to Use.

In the literature, many games (Hakulinen, 2011; Lee et al., 2013; Tili et al., 2016; Venigalla & Chimalakonda, 2020) have been evaluated using a questionnaire-based user survey combined with the TAM model. TAM has been widely used over time to evaluate learning games such as multimedia learning environment (Saade et al., 2007), ARTutor (Lytridis & Tsinakos, 2018). The two main
beliefs of TAM model, which influence the decisions taken by a user for adopting a new technology are *Perceived Ease of use (EU)* and *Perceived Usefulness (U)* (Davis, 1989).

Considering, the current scope of *ML-Quest* and factors associated with the TAM model, we found that TAM fits well for the evaluation of our game. Along with these two factors, TAM model also includes factors such as *Privacy concern*, *Perceived risk*, *Facilitating conditions* and *Subjective norm* (Im et al., 2008). But, since we are not dealing with any confidential user data, checking for *Privacy concern* and *Perceived risk* would be reluctant in the case of our game. Since, *ML-Quest* is a video game specially for K-12 students and can be played on any browser without the need of any supervision, evaluating for *Facilitating conditions* and *Subjective norm* is also not useful. So, we have excluded these factors and considered only the above-mentioned two relevant factors (i.e *Perceived Ease of use (EU)*, *Perceived Usefulness (U)*). *Intention to Use (I)* and *Correctness (C)* are also the important factors as *Intention to Use*, indicates whether the user would be willing to use the game in future or not and *Correctness (C)*, defines the degree of validity of the game, which is relevant in our case as we want to evaluate the relevance of the tasks assigned in each level compared to the concept taught. Thus, we evaluate our game based on four factors (i.e *Perceived Ease of use (EU)*, *Perceived Usefulness (U)*, *Intention to Use (I)* and *Correctness (C)*) using the TAM model.

![Image](image.png)

**Figure 5.** One of the volunteers of the survey participating in playing the game based on which survey form will be filled for our evaluation.
The survey was conducted in two phases. In the first phase, to test the knowledge gained by students we conducted experimental and control group based study. Students in the experimental group were asked to play the game as shown in Figure 5 and answer the questionnaire consisting of 22 questions which include, 4 demographics questions as shown in Table 1, 12 questions covering all the 4 mentioned quality factors as shown in Table 3 and 6 questions covering all the 3 concepts taught through the game as shown in Table 2. Students in the control group were taught the same concept as present in the game through slides and were asked to answer the questionnaire consisting of 10 questions which include, 4 demographics questions as shown in Table 1 and 6 questions as mentioned in Table 2 to test their knowledge. In the second phase, students were explained the concept by the mentor while playing the game as shown in Figure 6 and asked to answer the questionnaire same as that answered by the control group in the first phase to test their knowledge after the concept being explained through the game by the mentor. The students were encouraged to interact with the authors for any queries corresponding to the game and the survey, and the queries were resolved during the zoom session, as shown in Figure 7.

The current version of ML-Quest has three-game levels and each survey question covering a particular TAM quality factor is applicable for all the levels. To evaluate learner’s satisfaction after playing the game, we use a 5-point Likert scale based questionnaire covering the TAM quality factors in line with the literature (Tlili et al., 2016; Venigalla & Chimalakonda, 2020).

6. Results
Initially, we approached sixty students and divided them equally into experimental and control groups. Out of the 30 students of the experimental group, 18 of them responded to the survey and out of 30 students of the control group, 23 of them responded. Total 41 higher-secondary school students participated in the user survey with 46% of them being female and 54% of them being male with no prior knowledge about ML concepts that are introduced in the game. Twenty-two percent of the participants are familiar with the term ML and 24% of them searched for the underlying processes in ML as shown in Table 1.

First Phase – Students of the experimental group were asked to play the game and answer the questionnaire, while students of the control group were taught the ML concepts through slides and were asked to answer the questionnaire.

After playing the game, experimental group participants were asked to fill the questionnaire consisting of 12 questions covering TAM quality factors by rating each question in the range of 1 (strongly disagree) to 5 (strongly agree). A score close to 5 is an indicator of better acceptance among the users, whereas a score of 1 indicates poor acceptance. Figure 8 shows the result of the user survey in terms of mean and standard deviation of each question, covering all the four quality factors.

The main aim of the game was to introduce the concepts to children in an educative and entertaining format. As shown in Figure 8, question U3, “Using ML-Quest enhanced my effectiveness in learning and understanding multiple principles of Machine Learning” has a mean of 4.11 and a standard deviation of 0.75. A mean value above 4 with a minimum standard deviation shows that most of the participants agreed to question U2, indicating the usefulness of the game. Hence, the game can be played by interested participants to get a basic understanding of some of the concepts in ML. The levels in the game have been built with variations in complexity and an interesting storyline which makes it interactive and engaging. The results show that the participants find the storyline engaging, which can be observed from the responses of question I2, “ML-Quest has made my learning interactive”, with the mean value of 3.83. Correctness has a mean of 3.55 and a standard deviation of 1.042, which indicates the validity of our game, and users agree that they are able to relate the level outcomes to the underlying ML concepts. Furthermore, to test the knowledge gained by students in the experimental group after playing the game and students in the control group after learning the concepts through slides, we asked six questions as shown in Table 3 covering three concepts (i.e. Supervised Learning, Gradient Descent and KNN Classification) and compared the result.
Results show that students who played the game performed better in the test compared to the students who did not play the game. While both groups have an average score of 3/6, 5% of the students in the experimental group scored 6/6 but none in the control group could score 6/6.

**Second Phase** – Students of the experimental group, who played the game and students of control group, who learnt ML concepts through slides were explained the same concept by mentor while playing the game. Results show that 100% of the control group students could improve their performance in the test with 36% of them scoring 6/6 which was 0% earlier. 88% of the experimental group students were able to improve their performance with 22% of them scoring 6/6 which was 5% before.

Overall, the survey results suggest that the students were satisfied with the game design and they could understand the core ML concepts through game without any prior knowledge. The added interest because of the gameplay and the storyline along with the challenges in the game creates an immersive experience and helps students relate to the experience and map a mental model of the specific concepts. Furthermore, a few suggestions and improvements have also been provided by the participants who played the game such as:

- “The animation of the game can be improved a little bit.”
- “Maybe make the levels a bit more difficult because the difficulty was quite easy and not much intriguing.”

| Demographic questions                                      | Percent (%) |
|------------------------------------------------------------|-------------|
| Gender                                                     |             |
| Male                                                       | 54          |
| Female                                                     | 46          |
| Prior knowledge about ML                                   |             |
| Yes                                                        | 22          |
| No                                                         | 78          |
| Inquisitiveness for ML                                     |             |
| Yes                                                        | 24          |
| No                                                         | 76          |
| Choice of the platform                                     |             |
| Laptop/Desktop                                             | 70          |
| Smartphone                                                 | 48          |

**Table 1.** Demographic questions asked in survey.

![Instruction for each level](image1)

![Level 1. Player following supervised instructions](image2)

![Level 3. Bob and heart](image3)

![Level 2. Red Man as enemy](image4)

![Slope/Gradient in Level 2.](image5)

*Figure 6. One of the authors teaching the audience about Machine Learning and also giving walkthrough of the game after the session and explaining the abstraction behind each level.*
### Table 3. Questions asked in survey to evaluate the game based on four quality factors.

| Evaluation questions                                                                 | Variable | Mean  | SD   |
|--------------------------------------------------------------------------------------|----------|-------|------|
| I think learning to use ML-Game is easy                                             | EU1      | 3.94  | 0.72 |
| I think becoming skillful at using ML-Game is easy                                   | EU2      | 3.83  | 0.85 |
| Using ML-Game would improve my understanding of the concepts in Machine Learning    | U1       | 3.5   | 0.92 |
| Using ML-Game enhanced my effectiveness in learning and understanding multiple principles of Machine Learning | U2       | 4.11  | 0.76 |
| Using ML-Game would make it easier for me to learn Machine Learning concepts         | U3       | 3.78  | 0.73 |
| Assuming I had access to ML-Game, I intend to use it                                | I1       | 3.56  | 0.78 |
| ML-Game has made my learning interactive                                             | I2       | 3.83  | 0.92 |
| Visualizations displayed by ML-Game are relevant to the concept taught at each level | C1       | 3.56  | 1.04 |

### Table 2. Questions asked in survey to test the knowledge about the ML concepts.

| Questions                                                                 | ML concept          |
|--------------------------------------------------------------------------|---------------------|
| What is the underlying idea behind Supervised Learning?                  | Supervised Learning |
| What is the key input for Supervised Learning?                           | Supervised Learning |
| What is the idea behind Gradient Descent Algorithm?                      | Gradient Descent    |
| In Gradient Descent how do we reach optimum point?                       | Gradient Descent    |
| How do we classify objects using KNN classification?                     | KNN classification  |
| Using underlying principle of KNN classification classify a fruit which is surrounded by 2 apples and 1 mango in its 3 nearest neighbors | KNN classification |
7. Discussion and limitations

The current version of ML-Quest aims to provide conceptual overview of the three ML concepts (i.e. Supervised Learning, Gradient Descent, KNN Classification) by motivating the player to apply those concepts in a simulated scenario through a set of challenges tasks and game elements. Though the game has been developed to address the younger generation specifically the K-12 students, it can be played by a wide range of enthusiastic audience as well. The main challenge while designing ML-Quest was mapping ML concepts to the gameplay and levels. A concept in ML such as Supervised Learning has many subsections such as the mathematical aspect, the weights, labeled test-cases,

- “Instead of using left and right keys, we can use mouse to control. It will be more convenient.”

Figure 7. Authors interacting with the volunteers for answering doubts related to survey procedure and the game.

Figure 8. Mean and standard deviation plots for factors of adapted TAM model in the questionnaire.
target variables, and many more. We focused only on the basic principle behind Supervised Learning without going into inner details, but we could add few more concepts, if we can figure out ways to integrate them in the game without burdening the players. ML-Quest uses scaffolding technique and gradually uncovers the black box as the player reaches the end of the level while incorporating engaging game elements. Other ML subsections could also be introduced into the game by identifying better metaphors through scaffolding. Another challenge during the game development is the level of representation that needs to be provided in order for the player to understand and build a mental model of the concept.

In our survey, one of the comments says “Maybe make the levels a bit more difficult because the difficulty was quite easy and not much intriguing”, but during our experiment we found that a few students were not able to complete the level in the given time constraint and found the game to be difficult. This shows the need to add personalization to the game for learners with different learning capabilities. There is also scope to find better ways such as visual animations to show learning outcomes at the end of each level. We are continuously improving the game based on feedback from players, and plan to add more characters, have more levels and find better metaphors.

8. Related work

With advancements in technologies, several techniques such as visualization, computational notebooks and games have been adopted to make learning more interactive (Sulmont et al., 2019; Voulgaris et al., 2021). Many studies have reported games to be helpful in introducing various educational concepts such as code debugging and computer architecture and it has been leveraged by many researchers in the field of learning (Lee et al., 2013; Tlili et al., 2016). Games are motivating and make learning more interactive, interesting and engaging (Sung & Hwang, 2018). Teaching concepts through game could promote computational thinking and help students to understand the concept with fun in a better way.

Wu’s Castle (Eagle & Barnes, 2008) is a 2D game to teach array and looping constructs. In this game, the player needs to write code to perform certain tasks and understand the concept through visualization. The results show that the students who played the game outperformed in the coding test compared to those who did not play the game. Similarly, there are several games such as G4D (Venigalla & Chimalakonda, 2020) and Gidget (Lee et al., 2013) to teach concepts such as debugging, Computer Architecture (Tlili et al., 2016), supply chain and logistics (Liu, 2017) and many more. These games were observed to make learning easier and understandable compared to the traditional way of learning for the students.

Considering, the societal impact of ML, there have been initiatives to include AI and ML into K-12 curriculum to promote computing education. von Wangenheim et al. (2020) designed an online course for K-12 students to introduce basic ML concepts by training ML model using Google Teachable Machine. However, the amount of literature or courses providing an overview on teaching ML to school students is minimal, mostly targeting undergraduate and postgraduate students which is evident from the surveys in the literature (Marques et al., 2020).

There have been a few attempts to introduce ML concepts to K-12 students through visualization and games. Chung and Shamir (2020) propose an approach to introduce basic concepts of ML to K-12 students by encouraging them to develop applications that could perform different tasks using web based tools such as “Machine Learning for Kids”, “Scratch 3” and “Lego Mindstorms EV3 robots”. Hitron et al. (2019) tried to introduce ML concepts to the school children using hand gestures through a hardware device for training a classification model. From the outcomes, they conclude that if the black boxes are uncovered, it would be easier for children to understand the world around them better.

There are various resources present in the literature indicating that there have been attempts to introduce ML concepts such as model training and testing through games (Giannakos et al., 2020; Parker & Becker, 2014). While True: Learn() aims to introduce ML relevant concepts and its use-
cases by implementing a scenario where player plays the role of an ML specialist, who performs different tasks such as image and voice recognition. Many other games aimed at teaching AI and ML concepts mainly focus on educating students to understand the potential of ML in solving societal problems and its different use-cases (Giannakos et al., 2020). Although there have been attempts to introduce ML concepts to students through games, ArtBot (Voulgari et al., 2021) is the only game we could find relatably close to our work. ArtBot is a 2D game which attempts to introduce certain core ML concepts such as Supervised Learning and Reinforcement Learning through visual programming to primary and secondary school students. The game ArtBot introduces these concepts through classification and various other tasks without any supporting explanations which were found to be overwhelming for a few students as reported in their survey. Hitron et al. (2019) in their study on introducing ML concepts to kids report that uncovering multiple layers of an unknown concept could overwhelm the students. So, there is a need for a balance between uncovering and black-boxing ML concepts. Thus, to overcome this issue, ML-Quest has been designed to focus on gameplay instead of burdening the students with the technical concepts and elaborate on the concept only at the end of the level in scaffolded fashion by relating them to the game to help students create a mental model of the ML concepts.

9. Conclusion and future work

ML-Quest attempts at introducing the definition and working (i.e conceptual overview) of three fundamental Machine Learning (ML) concepts to K-12 students without going into the intricate complexities. There are three levels in the game for teaching three different ML concepts namely Supervised learning, Gradient Descent and KNN Classification. The game uses scaffolding technique to help players understand the concepts and create a mental model for the same. The storyline of the game consists of a character who needs to perform quests in order to free her kingdom. The game is engaging and consists of various components to make it interactive.

ML-Quest has been evaluated based on TAM quality factors through questionnaire-based survey of 41 participants from higher-secondary school. The survey was conducted in two phases. In the first phase, students were divided into two group namely, control group and experimental group. Experimental group students were asked to play the game and answer the survey questions. Whereas, the control group students were taught the similar ML concepts through slides and then were asked to answer the survey questions. Results show that student who played the game performed better in the test than the students who did not play the game. In the second phase, all the participants from previous phase were explained the concepts by mentor while playing the game. Result shows that 100% of the control group students were able to improve their performance in the test while 88% of the experimental group students improved their performance. After a remote qualitative user survey, we observed that the majority of the learners are satisfied with the game design and agreed that the game has enhanced their understanding related to ML concepts.

Future works of the ML-Quest would focus on adding more ML concepts by integrating new levels with better visualizations. We also plan to increase the complexity of the game to make it more challenging and fun at the same time by including more user engagement along with multiplayer feature. The graphics of the game at each level could also be improved as suggested by our volunteers in the survey. Our survey also shows that a considerable number of students prefer mobile based games, thus we are planning to explore other platforms such as smartphone where the game can be played seamlessly.

Notes
1. https://unity.com/solutions/console-and-pc-games.
2. https://assetstore.unity.com/publishers/7659.
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Data availability statement
The game is made available for play online at https://i.simmer.io/@shobhi1310/ml-game.

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