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Adjei Amaniampong
Technical University of Dresden, Germany

Solomon Oyelere
Lulea University, Sweden

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Systematic Literature Review on Pedagogies and Visualization Tools for Machine Learning in K-12 Schools

Adjei Amaniampong, Solomon Oyelere

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Abstract

Though studies have been done on Machine Learning, almost all the studies focused on higher educational institutions, with little attention to K-12 educational settings. Those studies that focused on K-12 are scattered, making it difficult to specifically know which visualization tools best enhance Machine Learning in K-12 schools. This study, therefore, through a systematic literature review determines which visualization tools best promote Machine Learning in K-12 schools. The study specifically considered, barriers to the use of Machine Learning in K-12 schools, visualization tools for Machine Learning in K-12 schools, and pedagogical strategies that benefit the teaching and learning of Machine Learning in K-12 schools. The study sourced articles from Scopus and the Web of Science database after applying the inclusion and exclusion criteria. Data from the articles were extracted based on the PICO framework and their quality was assessed using the Critical Appraisal Skills Programme (CASP) model. The barriers to Machine Learning in K-12 schools include a lack of information about the development and usage of the tools, selection, and coordination barriers, lack of attention to machine learning by educational stakeholders, and programming demands. Appropriate visualization tools for Machine Learning in K-12 schools include MLflow and NN-SVG. Though there exist numerous approaches for teaching ML in K-12 settings such as active learning, inquiry-based, participatory learning, and design-oriented approaches, the best pedagogy that supports machine learning in K-12 schools as per existing literature is participatory learning. Teachers need to acquire the appropriate and specific information and technical know-how or skills about machine learning for promoting visualization lessons in K-12 schools. All teachers should be sensitized to adopt participatory learning pedagogy to enhance the effective use of machine learning in K-12 schools. Machine learning should be integrated into teaching and learning in K-12 schools since it is ideal for visualization and experimentation, which are inevitable for effective teaching and learning in K-12 schools.

Introduction

Artificial Intelligence (AI) is infused into several devices and services that are part of our daily lives, such as healthcare, education, military, and autonomous vehicles. therefore, its overarching significance in today's education cannot be over-emphasized. Many other branches of AI, such as Machine Learning (ML), are already receiving attention in the curricula of undergraduate programs from several universities, and even in some high schools, as part of an extracurricular pensum (Abel et al, 2020). However, the process of learning ML can be considered a significant challenge for students due to several variables, such as lack of mathematical background, new technologies, and/or computer science knowledge. According to Rattadilok et al. (2018), teaching ML is not trivial, and there have been some key challenges commonly encountered in the teaching process such as the level of engagement and the willingness of the students to learn new technologies, which are critical for success. The appropriate set of topics selected to be taught for a specific group of students according to its standard level of education is a crucial factor for the motivation of students in any field and for teaching ML, due to the popularity of the subject and the number of people of varying ages interested in obtaining knowledge related to it (Abel et al., 2020).

Lately, AI, and in particular ML, has been one of the most requested skills in the industry, and teenagers are looking at this field as a potential career for their future. However, adapting the ML curriculum from higher to secondary education through to K-12 system is limited to the tools available that allow students to learn without having a specific background in computer sciences. For instance, typically required skills are at least a medium level of experience in programming and a solid background in mathematics and statistics. Aside from the fact that learning programming can be a fun experience, sometimes a young student does not have an affinity for the Information Technology (IT) world and does not need full exposure to programming but may want to learn ML as a starting point to get into the IT field. This calls for the training of citizens who know to be users and creators of intelligent solutions, this could be done through popularizing a basic understanding of ML technologies through appropriate tools and teaching strategies." (Kandlhofer et al., 2016; Touretzky et al., 2019a; Wong et al., 2020) Yet, teaching basic AI (including ML) ideas and techniques has historically been done solely in higher education (Torrey, 2012). Though computing education is more and more being included in K-12 worldwide, these programs seldom cover AI content at this academic stage (Hubwieser, 2015). Studies have however shown that kids can learn ML ideas from a comparatively young age (Hitron et al., 2019). This incorporates a comprehension of essential ML ideas, for example, learning algorithms and basics of neural networks just as the constraints and ethical concerns identified with ML. What is more, for students to become users of AI and makers of intelligent solutions, this requires showing the use of these ideas, for example, creating image recognition acknowledgment models. As noted by Sanusi et al. (2020) pedagogical approaches and strategies that are in existence as revealed by the literature review are mostly adopted in higher education institutions (HEIs) to enable the teaching of machine learning concepts. This calls for an imperative approach toward paying attention to ML concepts at the K-12 level. Even though there exist numerous tools directed towards visualizing ML concepts, they are still black-boxed as learners lack the opportunity to scrutinize, adjust meta-data, and see the real operations behind the ML decisions and responses. Students are still considered users instead of being actively engaged and treated as co-designers of the ML applications. These visualization tools are also intended for higher learning institutions as those at K-12 are not considered in the design and application process. For effective learner engagement, building learner trust, promoting social learning, and putting the learner at the center stage of the teaching and learning process at K-12, there is the need to white-box the black-boxed algorithms and help learners to visualize the abstract ML operations. This has left a big gap both in research and practice at the K-12 level, especially in developing countries such as Ghana.

Even though there have been efforts towards the development and implementation of effective curricula for the teaching and learning of AI in schools worldwide, the K-12 schools have received limited attention and developing countries such as Ghana are no exception. Ghana has many challenges in the education sector where the use of AI could be beneficial, sometimes even more than in other places, Among these challenges are: a shortage of teachers, especially in the area of STEM, lack of infrastructure, graduate unemployment, and school dropout. However, these challenges could be addressed through effective curriculum design, a well-structured pedagogical approach, well-trained teachers, and well-resourced learning centers from the K-12 schools through to the university level. Ghana being the first country in Africa to establish the AI Innovation Centre, (Adeoye,2019) with support from Google, can harness the inherent potential of AI education if attention is directed not only to the higher learning institutions but also the elementary levels in the same vein. Learning of concepts evolves and becomes part of the learners' developmental life if introduced at the early stages for school-going children. It is therefore imperative for practitioners, educators as well as researchers to shift focus on the effective techniques, approaches, pedagogies, and theoretical frameworks that could efficiently enhance the teaching and learning of AI at K-12 levels as little or no literature exist in Ghana. It should be noted that children appreciate the opportunity to become designers and makers of their applications (Vartiainen et al. (2020) and therefore enjoy the learning process if they are made an active part of the teaching and learning process. While today's children are active users of different ML-based services and applications, they seem to be in rather passive roles, and they do not know how the mechanisms of these services work and how ML can be utilized for different purposes (Pangrazio and Selwyn, 2019; Valtonen,2019).

The main goal of the current study is to explore and report on the various teaching methodologies and Visualization tools that have been applied in the teaching and learning of ML at the K-12 level over the past decade. A systematic Literature Review that applies the PRISMA approach was used to conduct this research. The objectives of this study are as follows:

i. To identify the barriers to machine learning in K-12 schools.
ii. To explore the various visualization tools used in teaching ML at K-12.
iii. To identify pedagogical strategies applied in the various visualization tools in existence.

Research Questions

i. What are the barriers associated with the teaching and learning of ML at K-12?
ii. What are the various visualization tools that have been developed for teaching ML at K-12?
iii. What pedagogical strategies have been applied in the various visualization tools in existence?

The ensuing parts of this paper will be organized as follows: section 2, summarizes a set of related works and provides the motivations behind this project, and section 3 presents the details of the review process. Section 4 provides an analysis of the results obtained through the review process. Section 5 examines the results obtained from this analysis. Finally, Section 6 concludes the article and suggests future work.

Literature Review

This section focuses on the explanation and review of key concepts, such as visualization tools, and the approach of artificial intelligence with an emphasis on machine learning, K-12 education, machine learning in K-12 schools, and pedagogy in k-12 schools.

The K-12 Program mandates that all pupils entering Grade 1 should have compulsorily undergone kindergarten or pre-school and the secondary level will add two more years, that is the senior high school. According to DepEd (Department of Education), K-12 Program has the following features: (1) making curriculum relevant to the learners, or contextualization and enhancement; (2) building proficiency through language, or mother tongue-based multilingual education; (3) integrated and seamless learning, or spiral progression; and (4) gearing up for future, or senior high school. The K-12 Program provides sufficient time for mastery of concepts and skills, develops lifelong learners, and prepares graduates for tertiary education, middle-level skills development, employment, and entrepreneurship. From the point of view of the government, K-12 is the appropriate response to address the century-old problem in education as well as being globally competitive (Cabansag, 2014). K–12 education system is pre-tertiary education from kindergarten through grade 12. kindergarten is required due to the dominance of research citing the long-term learning and social benefits of school readiness programs; and 12 years of primary and secondary schooling due to the time needed to acquire the knowledge and skill sets necessary for 21st century university education, postsecondary training, or decent work Sarvi et el (2015). Silliman and Schleifer (2011) emphasized the purpose of K–12 education as not only to teach academics, such as math and science but also to prepare students for work and to be good citizens. The study further shows that K–12 education has a lot of responsibilities for ensuring workers have the skills and education they need to be successful in today’s economy. Regarding what students should learn in K–12 education, in terms of career readiness, most Americans support offering more career skills classes, and most would favor having more career or skill-based classes over having more honors classes Silliman and Schleifer (2011). Education researchers and other stakeholders called for more innovation in K-12 education, leveraging technology in the classroom and experimenting with different organizing models for schools, as a means to increase quality Chatterji (2017). With the advancement of learner intake coupled with its limited infrastructure, K-12 learners are also permitted to choose homeschooling. The advocates of this system assert that it is at least as successful as conventional classroom-based education and base their support for this type of K–12 education on the results of empirical research on e-learning. Following a list of benefits for the system, they assert that K–12 instruction is a good alternative to traditional schooling (Buy, 2001). Contrarily, many who are against K–12 homme education base their arguments on problems including the absence of eye contact between teachers and students and how it affects learning results, the challenge of preventing cheating on exams, the challenge of determining students' true identities, and more (Dreyfus, 2001). There may be no restrictions on time or place for K–12 schooling, which indicates that there is a lot of freedom in terms of access to instructional resources. Through this flexibility, the students will be able to control their own time in a way that works with their schedules. A student who, figuratively speaking, is not a "morning person" can move his class schedule to later in the evening, whereas a "morning person" can take his courses in the morning. Due to the rigid timetable that students must follow, this is almost unattainable in traditional schooling (Dreyfus, 2001).

Machine Learning in K-12 Education

The topic of machine learning examines how computers can replicate or actualize human behavior. The main goal of acquiring new information or skills is to organize knowledge in such a way that it may develop itself gradually. Artificial intelligence is centered on machine learning. It is the main mechanism through which the computer is given intelligence. Machine learning develops each type of study theory and study methodology, studies the general algorithm, conducts theoretical analysis, and sets up study systems that have particular applications facing the duty. It does this by establishing the computation model or the understanding model by the study framework of humanity as revealed by physiology and cognitive science. The AI for K-12 Working Group (AI4K12) was established to create recommendations for instructing K–12 pupils about artificial intelligence. A branch of artificial intelligence called machine learning (ML) studies how to enable computers to learn without explicit programming (Mitchell, 1997). To generate forecasts or choices without being explicitly programmed to do so, machine learning algorithms create a mathematical model based on sample data. The importance of teaching machine learning in K-12 settings cannot be overemphasized. Wan et al. (2020), Tedre et al. (2017), Dwivedi et al. (2021) and Marques, Wangenheim and Hauck (2020). Wan et al. (2020) found that the face-overlay metaphor can inform the design of future technologies that support the learning of similarity-based ML methods such as k-nearest neighbor classification, information retrieval and anomaly detection. Wan et al. (2020) further noted that SmileyCluster system can positively support the learning of k-means clustering, which is centered around similarity comparison and global understanding. Tedre et al. (2017) also indicated that machine-learning students know how their world works and that machine-learning technology brings about some new ethical concerns to be included in computing education. Similarly, Dwivedi et al. (2020) noted that children benefit from being exposed to the confidence scores of machine learning and machine learning helps to promote experimentation. Marques, Wangenheim, and Hauck (2020) noted that teaching ML in school can increase understanding and interest in this knowledge area as well as contextualize ML concepts through their societal impact. Students must learn how to create ML apps to master machine learning capabilities at the application level and provide intelligent solutions (Kahn et al., 2018). However, because machine learning is a sophisticated field of study, beginners to ML may find it challenging (Sulmont et al., 2019). Additionally, because K–12 children frequently lack prior computing expertise, it is crucial to precisely determine the order in which learning objectives are to be attained. Consequently, learning ML should start with lower-level abilities and work its way up. On the other hand, it is crucial to avoid staying at lower levels because doing so might impede the growth of creative abilities, which calls for unstructured, open-ended learning activities. Additionally, implementing a "computational action" strategy (Tissenbaum et al., 2019) is essential to give learners the chance to be imaginative and convey themselves through the use of ML. This strategy enables students to learn machine learning concepts while producing purposeful artifacts that directly affect their lives and their societies (Kahn et al., 2020).

Age-appropriate tools that have a low entry point and a high ceiling are needed to enable such learning by generating ML models. This will make it simple for beginners to get started and allow them to work on progressively more complex tasks (Resnick& Silverman, 2005). They should also encourage and recommend a variety of ML models, like as those for music comprehension and the recognition of pet photographs, to enable students to work on projects that are inspired by their hobbies and ambitions (Resnick& Silverman, 2005). To maximize the potency of ML in K-12 settings, it is important to look at the that have been employed in the teaching and learning of this all-important technological advancement.

Approaches to teaching and learning of machine learning in K-12 settings

Artificial intelligence (AI) has become a hot topic of conversation and has grown significantly in impact across several industries and areas. Education systems are challenged by how AI affects the workplace and daily life (Koo & Liew, 2020). Understanding and using AI tools, strategies, and procedures as well as being able to assess and recognize the long-term advantages, societal, and ethical elements of AI are all becoming essential 21st-century talents (Touretzky, 2019). Traditionally, universities have been the places where these AI abilities have been taught. The goal of AI education at the K–12 level has recently been pursued by several organizations and programs.

One formally recognized method of teaching AI is AI Singapore (AISG) (Koo and Liew, 2020). Its main objective is to increase Singapore's competitiveness in AI. It was started by Singapore's National Research Foundation. A substantial role is also played by research and industrial education. AI K12 education is covered by two programs. To enhance instructors' abilities and reach out to schools, both adhere to the train-the-trainer philosophy (Koo and Liew, 2020). Young people between the ages of 9 and 12 are the target audience for the AI4Kids program, which focuses on the fundamentals of AI with a strong relationship to coding (Koo and Liew, 2020). From introductory training, teachers can earn credentials. Compared to AI4K12, the initiative's scope is more constrained because the themes are more technologically focused, and no universal curriculum is anticipated. The AI4Students program is geared for college and high school students. This effort, which works with the Business Data Camp, is primarily concerned with big data and data analysis. The effort serves as a sort of stand-in for Data Camp’s current courses and its learning analytical tools.

Additionally, the Japanese government has chosen to publish a strategy for developing students' data literacy and IT skills in grades K–12 (Duan& Gong, 2019). Following that, a study and policy were released by the Ministry of Education, Culture, Sports, Science, and Technology that focused on how students may use artificial intelligence technology to create economic value. The Japanese national curriculum requires computer science to be taught beginning in primary schools by the year 2020, (Kanemune et al., 2017). The guide's objective is to train K–12 children to comprehend and use AI-enhanced technology in the future, preserving Japan's competitiveness as one of the top nations in the AI-driven globe. Additionally, it encourages K–12 children to comprehend and be conscious of AI ethics (Eguchi et al., 2021). A collection of AI curricula and tools was proposed to fit with the five Big Ideas in AI and to help students understand how AI works by giving them firsthand opportunities to create artifacts and creations that are enhanced by AI (Eguchi et al., 2021).

To enhance AI competitiveness, South Korea also adopts a formal strategy that includes offering approved guidelines and resources. For each grade band, the learning is diverse and arranged around important subjects like comprehending AI, AI, and data, or the application of AI (Kim et al, 2021). Data science and machine learning are given a lot of attention in the recommendations, and coding is strongly linked to these topics as a learning strategy. The South Korean project is covered in further detail in the following documents (Kim et al, 2021).

To encourage young people to learn about AI, Australia takes a different approach. Instead of being established as an independent AI curriculum, AI subjects are mapped on the broader Digital Technologies portion of the Australian Curriculum, which outlines the expectations on learned abilities of students in different grades. Concepts from AI, such as representations, data, or algorithms, may be easily included in the national curriculum using the fairly open description of those elements that are dedicated to understanding and constructing digital systems (McLoughlin, 2017). For instructors in elementary and secondary schools, the Computer Science Education Research Group's (CSER) MOOCS program offers a selection of introductory MOOCs to AI. The low-key workshops are designed to equip instructors to begin incorporating AI into the classroom. As an introductory course, the curriculum places a lot of emphasis on machine learning-related subjects that are simple to understand. The different member nations of the European Union (EU) are responsible for their educational systems. The European Commission places a lot of emphasis on research and business in the field of artificial intelligence (Martin et al, 2021). A European approach to quality and trust in education is highlighted in the “White Paper on Artificial Intelligence: a European Approach to Education”, but no comprehensive strategy for AI education K–12 is provided (Martin et al, 2021). Even though curricula are not being developed at the EU level, programs like AI Basis for Schools, which is part of European Code Week, attempt to train teachers in the fundamentals of AI so they may include it in their respective national curricula (to the extend the curricula allow such an integration). The different member nations of the European Union (EU) are responsible for their educational systems. The European Commission places a lot of emphasis on research and business in the field of artificial intelligence (EDLRIS, 2021). Though employing AI to enhance education and educate people about AI is discussed in the White Paper on Artificial Intelligence—A European Approach to Excellence and Trust Education, no comprehensive strategy for AI education in grades K–12 is provided (Williams et al, 2019). Although curricula are not being developed at the EU level, there are efforts like AI Basis for Schools, which is a part of European Code Week, that attempt to train teachers in the fundamentals of AI so they may include it in their national curriculum (to the extend the curricula allow such an integration).

Even though the pedagogical framework and curriculum restructuring for the teaching and learning of ML at the K-12 level is an emerging research, there exists a variant literature for strategic design and improvement for the future. Zhou, Brummelen, and Lin (2020) reviewed 49 of the existing frameworks and noted a polarizing trend in some of the various frameworks such as how over half of the works leveraged learners’ interests, created a low barrier to entry, promoted transparency, utilized explainability, contextualized data and provided students with opportunities to program. The authors noted that fewer than 15 of the 49 works utilized design considerations, milestones, critical thinking, and new perspectives, while fewer than 10 utilized embodied interactions and unveiled a few concerns about the tool. Three of the works however utilized identity, values & background, acknowledging preconceptions, and support for parents.

Hoffman, Rosato, and Morelli (2019) stated that inquiry-based learning approaches for computer science education have the potential to improve student engagement, student achievement, and student attitudes toward computer science education. Similarly, game-based learning approaches that motivate students with compelling virtual worlds can be used to create engaging AI learning experiences in K-12 classrooms (Wang and Johnson, 2019). Efforts are being made to explore how to incorporate AI more intentionally at the K-12 levels (Touretzky et al., 2019). Since problem-based learning and game-based learning both can support student engagement and achievement, there is a need to integrate these instructional approaches for promoting ML education at the upper elementary school level (Hmelo-Silver et al., 2018). Vartiainen et al, (2020) state that "when students are made to co-design and make ML applications, they are not limited by culturally dominant stereotypes as to the kind of personalities who can do computer science". Instead, the results of their study implied that co-designing personalized artifacts was also connected to the perceived ownership of learning and may support students in developing one's identity as computational designers. Sanusi and Oyelere (2020) study suggests that learner-centered approaches such as active learning, inquiry-based, participatory learning, and design-oriented learning could be suitable for teaching machine learning in K-12 settings.

Collaborative learning as a pedagogy for teaching K–12 machine learning is emerging from the literature (Sperling and Lickerman, 2012). Researchers have examined the effectiveness of collaborative learning as a method to promote learning (Fakomogbon and Bolahi, 2017) (Luna, 2015) asserts that learners engage in higher-order thinking skills including managing, organizing, critical analysis, problem-solving, and producing new information through collaborative learning. According to Fakomogbon and Bolaji's (2017) study, information sharing through collaborative learning can improve motivation, academic results, and engagement. The research by Mariescu-Istodor and Jormanainen (2019) demonstrates that high school pupils can come up with original and surprising ideas and that the type of collaborative working style adopted is appropriate for them.

Machine learning may be taught to K–12 students using active learning pedagogy. In undergraduate settings, it demonstrates that via learning strategies, students have better identified the value of machine learning as a data-driven strategy for solving real-world issues. This is supported by recent research by Huang and Ma (2018). It also altered the way that students perceived difficulty and encouraged them to take on more complex arithmetic and data analysis assignments. Students can be involved in higher-order thinking activities through active learning. The influence of inquiry-based learning (IBL) on primary scientific teaching has been tremendous in K-12 education. IBL work benefits students' academic performance, according to a recent study, and the practice is becoming more common (Park, 2015). If students are sufficiently supported, research repeatedly demonstrates that inquiry-based learning may be more successful than other, more expository educational techniques (Lazonder and Harmsen, 2016).

In the evolving context of teaching and learning in the twenty-first century, individualized learning is becoming the way forward for global education (Stewart, 2017). According to (McLoughlin, 2013), information is frequently discussed with the learners and necessitates the active direction of the student rather than being written and pre-packaged by an instructor. It was further emphasized that personal learning environments (PLEs) are learner-centric, providing relevant and timely learning opportunities by enabling people to select, incorporate, and develop knowledge using different software, assistance, and alternatives based on their needs and situations. This contrasts with teacher-directed curricula, which are learner-centric.

Participatory learning is another method that is appropriate for K–12 instruction. According to Fisher (2013), the goal of participatory learning is to give students the tools and opportunities they need to participate in social interactions, build consensus among various stakeholders, and frame and resolve real-world problems that matter to them personally. It is not about giving students information that has already been digested. Additionally, it develops settings that provide kids the chance to investigate actual occurrences in a way that is motivated by their interests and inquiry-based (Vartiainen et al, 2018).

An interactive learning strategy can be used in K–12 classrooms. With or without the use of technology, interactive learning engages students more deeply and increases their retention of information by fostering their ability to think critically and solve problems. Students are encouraged to direct their learning and create meaning using an interactive learning approach (Sessoms, 2008). While lectures are turned into dialogues and students and teachers become collaborators in the process of learning, interactive learning revitalizes the classroom for both parties (Sessoms, 2008). Sperling and Lickerman (2017) offer an innovative program for high school students in software engineering that includes courses in machine learning and artificial intelligence. Making pupils actively participate in their learning was suggested as part of the educational philosophy.

Machine learning may be taught to K–12 children using a paradigm called design–oriented learning, which sees learners as knowledge creators. Papert envisaged a society in which children design, produce, and program artifacts, which is comparable to design-oriented learning, according to Resnick and Robinson (2017). According to Vartiainen's (2017) research, students' prospects of being active participants in their own lives and learning in contexts outside of the classroom would be improved by a design-oriented learning system. According to Roth and Lee (2006), the educational method is linked to students' perceived ownership of their learning and their areas of interest. It also gives students the chance to develop various types of solutions to issues they see as relevant (Krajcik and Blumenfeld, 2006). Young children may participate and become engaged concerned citizens in the co-developed learning experience and the generation of local knowledge through design-oriented pedagogy (Anu, Jorma, and Sinnikka, 2014). Lai and Chan's (2014) study in a machine learning course demonstrates improved knowledge, less uncertainty, more active reaction, and a greater classroom environment using the design approach. Additionally, Mariescu-Istodor and Jormanainen's (2019) employed design-oriented techniques to develop a machine learning approach for K–12 which enabled students to successfully were able to deploy an ML system.
Sanussi et al. (2020), summarized the various pedagogies used in the teaching and learning of ML in the K-12 context as depicted in Diagram 1.

The study described the various pedagogies applied in teaching ML in the K-12 context and identified as well as described the potential pedagogical frameworks suitable for machine learning in K-12 settings. The literature survey revealed different pedagogical tactics such as problem-based learning, project-based learning, and collaborative learning. The revealed pedagogies suggest that learners-centered approaches such as active learning, inquiry-based, participatory learning, and design-oriented among others will be suitable for learning in K-12 settings Sanusi et al. (2020). Furthermore, they suggested experimentation as one of the best approaches to ascertaining a suitable pedagogical framework for teaching and learning ML in K-12.

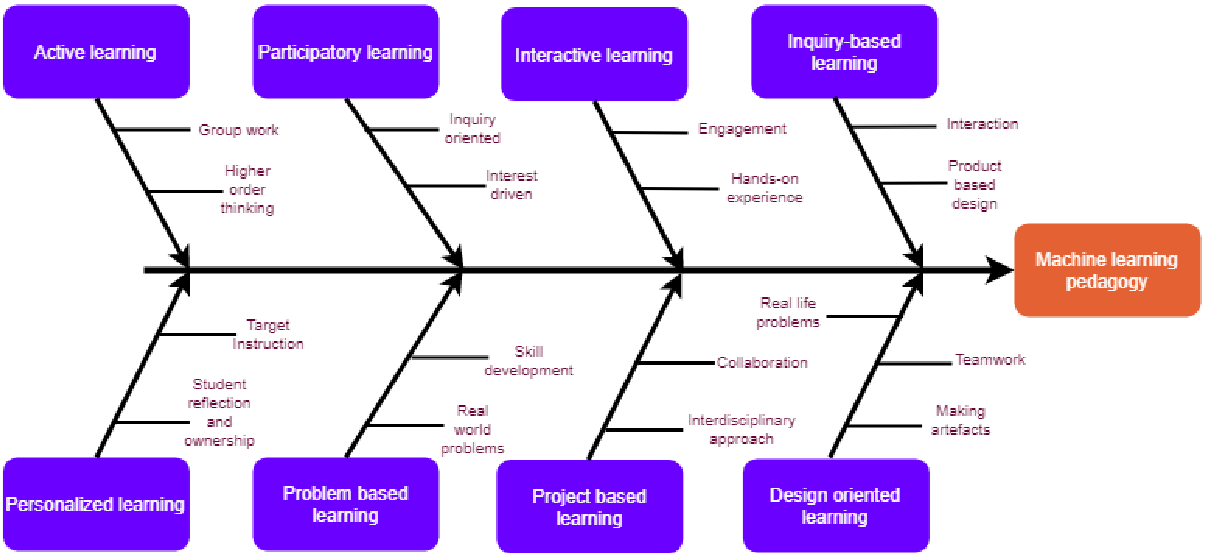

Diagram 1. Fishbone summary of Pedagogies for Teaching ML at K-12 Sanusi et al, (2020)

Visualization Tools

There exist several visualization tools for the teaching and learning of ML at different levels of education. These include Derrac et al. (2011) who propose KEEL as a software for teaching data mining (DM). KEEL is an open-source application based on Java and it allows learners to access AI algorithms with visualization for feedback on the progress of the algorithms and also enables learners to access the final results from the same user interface. This doesn’t require extensive programming knowledge from the users. Chiang et al. (2007) also adopted a traditional video game with ML technology to motivate students in the teaching and learning of ML concepts. This used a simple interface to demonstrate a real application through a popular character. This motivated and brought the attention of learners. Rattadilok et al. (2018) in their bid to promote learner motivation and engagement also proposed the idea of adopting gamification for teaching ML topics integrating the learning process into a game situation, creating context while learning, offering rewards and using good criteria at the time to define the goals of his proposal, exposing different concepts such as machine teaching and gamification. Relatedly, Aquayo et al. also adopted a visualization tool for cybersecurity education focusing on the development of a framework standardized to fit different kinds of topics focusing on IT education (Aguayo et al. (2019).

Tools that give a graphical representation of information or data are known as visualization tools. Users' ability to make sense of information is enhanced by interactive visualizations and analytical tools. Examples of applications for these tools include document investigation and analysis (Stasko, Gorg, & Liu, 2008) and the examination of simulation findings in science (Keim et al, 2008). Recent research in the field of visual analytics is looking at the advantages of tools and algorithms that can infer a user's purpose from their explorations and then modify the structure and content of a visualization to match the user's mental model (House et al, 2015). Because the system learns from and adapts to the user, the analytical process may be made more effective, therefore. A variety of visual analytics solutions offer live data projections that change in response to observed user behaviors (Kwon et al, 2017). Opportunities for learning from interactions are introduced by scientific visualization, including analysis of data ensembles, interactive visual querying of nonlinear solution spaces, the in-situ study of large-scale data, and data foraging across extremely vast data (Coffey et al, 2013). TensorBoard, DeepGraph, Scratch, Snap, and App Inventor are a few of the programs that are crucial for machine learning in K–12 education. Integration with text-based languages like Python is also not widely supported by utilities.

Systematic Review Methodology

The section is subdivided into the systematic review where the systematic review is justified, the search strategies, justification of the inclusion and exclusion criteria, data extraction, ethical issues, and reliability and validity of the instruments used in the study.

Literature Review Approach

There are many other types of literature reviews, but four are typically used by academics. Scientific literature review papers are methodological studies that gather research findings from databases and feature a significant objective and theoretical discussion of a certain subject or issue. These four primary types of literature reviews include meta-analyses, systematic literature reviews, conventional or narrative literature reviews, and meta-synthesis (Arshen and Dashen, 2014). Narrative and systematic literature reviews are the two most common types of review papers, and they each have unique characteristics and objectives. The publications known as narrative literature reviews describe and examine the status of the science of a certain subject or issue from a theoretical and contextual perspective (Rother, 2007). The types of databases and methodological techniques utilized to perform the review, as well as the criteria for including generated articles during database searches, are not listed in these sorts of review publications (Bernardo, Nobre, and Jatene, 2004). A narrative review includes a critical evaluation of the literature found in printed books and online or print journal articles.

Systematic reviews, on the other hand, are well-planned reviews that use a systematic and clear technique to locate, select, and critically assess the research findings included in the literature review. They seek to address specific problems by offering solutions. Since systematic literature reviews are undertaken following strict scientific procedures, they are regarded as unique works(Jahan et al, 2016)

As the name suggests, systematic reviews often comprise a thorough and detailed plan and search method devised a priori, to decrease bias by locating, evaluating, and summarizing all pertinent papers on a certain issue. A meta-analysis component is frequently present in systematic reviews, and it involves the use of statistical methods to infuse data from various publications into a single quantitative approximation or overall effect size (Petticrew & Roberts, 2006). Although systematic reviews are published in academic journals, they are also promoted and disseminated through organizations and databases. For instance, the Cochrane Collaboration is a well-known organization that promotes the use of systematic reviews. The Preferred Reporting Items for the Systematic Review and Meta-Analyses (PRISMA) approach is used in this paper. The PRISMA framework refers to a set of guidelines or steps developed by Moher, (2013). These steps are useful for systematic literature reviews, critical literature analyses, and meta-analyses. The PRISMA tool or framework uses a set of methods to systematically search papers and literature for review-based studies. In addition, PRISMA is also based on the formulated inclusion and exclusion criteria in any type of study that systematically assesses the quality of chosen papers and either includes the study or excludes the study. As a result of this, PRISMA is the preferred review approach since the main goal of this paper is to review existing literature on visualization tools used in teaching ML at the K-12 level. The PRISMA checklist was created to help systematic reviewers explain the purpose of the systematic review and its findings in a transparent manner (Page et al, 2021). Over the past few decades, improvements in the methodology of systematic reviews have made it necessary to update methods to address contemporary problems (Gurevitch et al, 2018). Since the release of the PRISMA checklist, several advancements have been made in the way systematic reviews are conducted. For instance, technological advancements have made it possible to employ machine learning and natural language processing to find pertinent evidence (O'Mara-Eves et al., 2015). The PRISMA checklist includes 17 elements that are suggested for systematic reviews, along with extra reporting instructions for each item (Liberati, Altman, and Tetzlaff, 2009). Studies that focus on Machine Learning in K-12 schools such as Zafari, Bazargani Sadeghi-Niaraki, and Choi (2022) effectively applied PRISMA.

The study will widen its scope to cover policies that are essential in encouraging machine learning in k-12 schools and the various approaches applied in the ML at K-12. Therefore, grey literature on these policies will be included in the study to understand the role these policies play in enhancing the use of visualization tools for machine learning among k-12 schools.

Search Strategy

Creating a search strategy is a laborious process that needs constant evaluation and improvement since the effectiveness of the keywords or key terms used in the search is defined by the search results (Aromatis & Riitano, 2014). It will take different amounts of time to look for a systematic review. The review methodology depends on the review question, the depth of the evidence, and the size of the suggested search. The search for the literature will also start on databases including Education Research Complete, JSTOR, IEEE, ERIC, ACM, XPLORE DIGITAL, and Google Scholar. These databases, in particular Education Research Complete and Google Scholar, contain a large selection of publications focused on education that will be helpful for the research (Aromatis & Riitano, 2014). The searches take place between January 2012 to July 4 and July 31, 2022.

This part of the systematic review method's main goal is to ensure that the review contains the best available evidence on the subject. The search is conducted in the online databases in such a manner that it seldom retrieves all the relevant material, and it is supplemented by looking through the bibliographies on pertinent search results (Sampson et al, 2008). To give a straightforward method of getting the necessary literature, all the data were sought by simply keying in the names of the publications in the databases. The study will further make use of keywords such as ‘visualization’ ‘tools’ ‘teaching’ and ‘machine learning’. The study further makes use of Boolean operators ‘OR’ and ‘AND’ to aid in searching the relevant information on distinct key terms. For instance, *Visualisation* ‘AND’ ‘*Machine learning’* and ‘*Machine learning’* ‘AND’ ‘k-12’ are used in the study to ascertain the impact that visualization tools have on machine learning among children in k-12 schools. The execution of the search started in July 2022 by the authors. At the initial state, a total amount of 1,340 were retrieved with 340 coming from Google and the rest from scientific databases. As a result of the volume of data retrieved, the author restricted the analysis to 291 most relevant ones. Based on the titles and abstracts of the selected papers, further filtering was conducted to remove duplicates and irrelevant publications. Based on this, a total of potential documents for our review were left with 62 artifacts. The inclusion and exclusion criteria as established beforehand were then applied to select the most essential ones for the study.

Inclusion and Exclusion Criteria

When developing excellent research procedures, the inclusion and exclusion criteria are a crucial prerequisite (Patino and Ferreira, 2018). The characteristics that potential subjects must have to be included in the research are referred to as inclusion criteria. The authors considered only English-language publications that aim at presenting visualization tools for the teaching and learning of ML at K-12 schools, excluding visual programming languages or tools for other purposes. As a result of the rapid evolution of the topic in question, and ML designs in general, we limited our search to tools designed within the last decade (2012-2022). We focus on tools that allow the creation of custom ML models, excluding tools for demonstration purposes. We also exclude any approach focusing only on the visualization of ML models or aiming at the complete automation of their development. Furthermore, we only include tools that have been developed or used for educational purposes in K-12. Consequently, we exclude any ML tool targeted exclusively for professional or adult end-users. We consider only articles that present substantial information allowing the extraction of relevant information regarding the analysis questions. Therefore, abstract-only or one-page articles are excluded.

Studies from educational and scientific databases and libraries in the field of computing, including ACM Digital Library, ERIC, IEEE Xplore Digital Library, ScienceDirect, Scopus, Web of Science, and Wiley as resources are meant to give comprehensive information on the subject at hand. A search on Google to find tools that have not been published in scientific libraries was also done, as it is considered acceptable as an additional source aiming at the minimization of the risk of omission especially regarding tools that may not yet have been published via the scientific databases (Piasecki et al., 2018). To further minimize the risk of omission, we also included literature found via backward and forward snowballing (Wohlin, 2014). Secondary literature has been consulted to complete the information on the encountered tools.

Definition of the Search String

Based on the research question, several informal searches were performed to calibrate the search string, identifying relevant search terms (Table 1). Synonyms were also included to minimize the risk of omitting relevant works. We did not include terms related to education as this text searches returned mostly articles related to the application of ML techniques for learning analytics or personalized learning, rather than being related to teaching ML concepts. To minimize the risk of omission, we searched for the search terms not only in the titles but also in the abstracts of the publications. The demographics are one inclusion criterion that will be important to the investigation. The demographic characteristics include, among other things, age, gender, and educational background. However, the focus of the study will be on studies that look at the age range of teachers who work in the k–12 grades. Therefore, the research will take into account studies with an age range of at least 20 years. Studies that look at pupils in the K–12 range will also be added. Such pupils will be successful in the study because they have sufficiently developed brains to handle machine learning at all stages, from the basic to the complex. The geographic area that the investigation covers will be another inclusion factor employed in the study. The research takes into account the environment in which it was conducted. Also, studies that involve college students and university students are all exempted from the study. This is because this study relies heavily on articles that have captured the use of visualization tools in teaching machine learning at the K-12 level. Any level higher or lower than the K12 level is absconded from the study.

Table 1. Search String for Each Source Search String

Source	Search string
ERIC	((abstract: “visual programming” OR abstract: “block-based programming” OR abstract: “GUI tool” OR abstract: “toolkit”) AND (abstract: "machine learning" OR abstract: "neural network")) pub year: since 2012
IEEE Xplore Digital Library	(("Abstract": “visual programming” OR "Abstract": “block-based programming” OR "Abstract": “GUI tool” OR "Abstract": “toolkit”) AND ("Abstract": "machine learning" OR "Abstract": "neural network")) Filters Applied: 2012—2022
ACM Digital Library	[Abstract: "visual programming"] OR [Abstract: "block-based programming"] OR [Abstract: "GUI tool"] OR [Abstract: toolkit]] AND [[All: "machine learning"] OR [All: "neural network"]] AND [Publication Date: (01/01/2012 TO 12/31/2022)]
Science Direct	Year: 2012–2022 Title, abstract, keywords: (("visual programming" OR "block-based programming" OR "GUI tool" OR toolkit) AND ("machine learning" OR "neural network"))
Scopus	TITLE-ABS-KEY ((("visual programming" OR "block-based programming" OR "GUI tool" OR toolkit) AND ("machine learning" OR "neural network"))) AND PUBYEAR>2010 AND PUBYEAR

Table 2. Number of Artifacts identified per Stage of Selection Source

Source	No. of search results	No. of analyzed artifacts	No. of potentially relevant artifacts	No. of Relevant artifacts
ACM	104	33	11	2
ERIC	182	24	09	2
IEEE	324	89	17	4
Science Direct	182	25	10	2
SCOPUS	178	32	08	2
Web of Science	208	26	08	2
Google	502,000	62	18	3

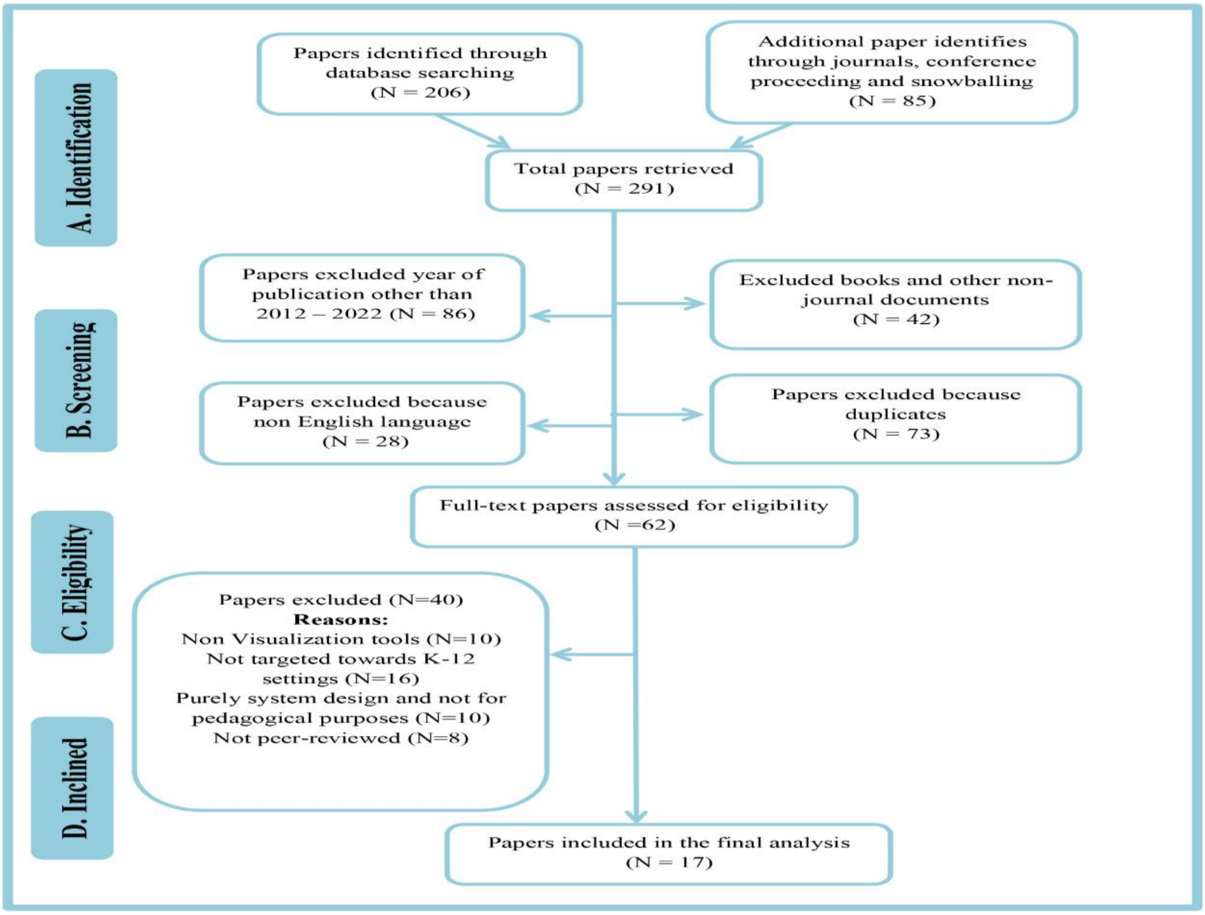

Figure 1. Systematic Review Process (Adapted from Moher, Liberati, Tetzlaff, & Altman, 2009)

Data Extraction

To save time and lower the margin of error, Carroll, Scope, and Kaltenthaler (2013) established that researchers utilize a form to submit their retrieved data. This approach, which has been supported for some time, involves using such forms to create datasets that are eventually made freely accessible and available for replication (Wolfenden et al, 2016). The location of the investigation, the technique that was employed, the study's findings, and its conclusions are all keyed into a Microsoft Excel spreadsheet for this study. The demographic characteristics of the respondents in the articles are taken into further consideration as part of the approach for the data that are being keyed. The study further deploys the PICO model in extracting data. The PICO is a short form for Population, Intervention, Comparison, and Outcome. According to Frandsen et al. (2020), the recall is much lower when the PICO is used as a search model for data extraction. The PICO model is therefore used since it is critical for extracting detailed information for the study.

Quality Assessment

Many appraisal instruments are used to assess the quality of a systematic review. Such appraisal instruments include the Newcastle-Ottawa Scale, Assessing the Methodological Quality of Systematic Reviews, and Quality Assessment of Diagnostic Accuracy Studies among others. This study makes use of the Critical Appraisal Skills

Programme as a tool for assessing the quality of this study. The JAMA users guide to medical literature from 1994 served as the foundation for the basic CASP checklist's randomized controlled trial and systematic review sections (CASP, 2018). A team of specialists was put together for each checklist to create and test the format (CASP, 2018). The 10 questions on the CASP checklist for systematic reviews are designed to help the reviewer approach problems methodically.

Data Synthesis

The systematic review goes beyond the subjective narrative tracking character traits of a narrative or traditional literature review, according to Munn et al. (2014). This is done through the process of retrieving, incorporating, and synthesizing data from multiple studies. According to Zachary et al. (2014), synthesized data in a systematic review are findings that are taken from studies that are essential to answering the question under consideration. There are various techniques for data analysis in systematic reviews, as Mekie and Taklual (2019) point out. The narrative synthesis is utilized in this work, nevertheless. The term "narrative synthesis" refers to a method for synthesizing data from several research that is based mostly on the use of words and texts to evaluate and present the data of the synthesis (Popay et al, 2005). The distinctive feature of narrative synthesis is that it uses a textual synthesis process to describe the results of the investigations (Popay et al, 2005). The information in this research is therefore thematically keyed based on the analysis that has been done. For data extraction and analysis, the study uses the Microsoft Excel program.

Findings

This section of the study describes the results of the review based on the journals selected for the implementation of the inclusive strategies as elaborated above. The study included in this report covered studies on machine learning barriers, visualization tools, and pedagogies applied in teaching ML at the K-12 level (see Table 2).

Table 2. Inclusive Studies

Authors	Article Title	Data Collection Method	Data Analysis Approach	Findings
Wangenheim, G. C., · Jean C. R. Hauck, R. C. J., Pacheco, S. F., Bueno, B. F. M (2020)	Visual tools for teaching machine learning in K-12: A ten-year systematic mapping	Data was obtained mainly through digital databases and libraries in the field of computing, including ACM Digital Library, ERIC, IEEE Xplore Digital Library, ScienceDirect, Scopus, Web of Science, and Wiley	Systematic review	Lack of information on how the tools have been developed and evaluated, although, the results of few explorative empirical studies indicate the usability and usefulness of these tools in K-12. Yet, there is still a need for more empirical research analysing diverse aspects of these visual ML tools to

Authors	Article Title	Data Collection Method	Data Analysis Approach	Findings
		with access via the Capes Port.		systematically evolve and improve these tools for better support of ML education in K-12.
Sarkar, A., Jamnik, M. &Spott, M (2015)	Interactive visual machine learning in spreadsheets	Data was collected through observation of tasks performed by participants	Data was analyzed with the help of the Kulesza et al.'s coding scheme.	BrainCel successfully exhibits properties desirable in interactive machine learning systems
Wan, X., Zhou, X., Ye, Z., Mortensen, K. C. and Bai, Z (2020)	SmileyCluster: Supporting Accessible Machine Learning in K-12 Scientific Discovery	Data was collected through observation of task performed by participants and interviews	The study analyzed interview scripts using the thematic analysis approach to determine the high-level themes of participants' answers	The face-overlay metaphor can inform the design of future technologies that support the learning of similarity-based ML methods such as k-nearest neighbor classification, information retrieval, and anomaly detection. Again, the SmileyCluster system can positively support learning of k-means clustering, which is centered around similarity comparison
Rodríguez-García et al., 2020	Learning ML A platform aimed at learning supervised ML for teaching ML in K-12	Secondary data	Experiment study	There have been significant issues with the learning of Supervised ML and these issues have not been given due attention in the literature to date, especially in the K-12 settings
Tedre, M., Toivonen, T., Kahila, J., Vartiainen, H., Valtonen, T., Jormanainen, I. & Pears, A (2017).	Teaching Machine Learning in K–12 Computing Education: Potential and Pitfalls	Secondary data	Experiment study	Machine learning provides to computing and automation a perspective that is markedly different from the perspective of rule-based computing and programming-based

Authors	Article Title	Data Collection Method	Data Analysis Approach	Findings
				computational thinking. Secondly, there is no consensus over the trade-offs necessitated by black-boxes, and there is a paucity of research on their effects. there is no agreement over the relationship between ML skills and knowledge and the multitude of skills and knowledge labeled “computational thinking”
Sanusi, T. I (2021)	Teaching Machine Learning in K-12 Education	Secondary data	Experiment study	Learners-centered approaches such as active learning, inquiry-based, participatory learning, and design-oriented among others are suitable for learning in K-12 settings
Dwivedi, U., Gandhi, J., Parikh, R., Coenraad, M., Bonsignore, E., & HernisaKacorri (2021)	Exploring Machine Teaching with Children	Data was collected through observation	thematic analysis	It was revealed that metrics such as confidence scores tend to serve as a proxy for children to judge whether the model was confused or unstable. Also, inviting children to swap and test their classifiers elicits collaborative observations and reflections and promotes experimentation
Marques, L.S. Wangenheim, C. G. & Hauck, C.R.J, (2020)	Teaching Machine Learning in School+D6	30 instructional units mostly focusing on ML basics and neural networks were used	systematic mapping study.	The results indicate that teaching ML in school can increase understanding and interest in this knowledge area as well as contextualize ML concepts through their societal impact.
Park, Y. & Shin, Y (2021)	Tooee: A Novel Scratch Extension	No	Experiment study	Teachers who did not give a high deployability

Authors	Article Title	Data Collection Method	Data Analysis Approach	Findings
	for K-12 Big Data and Artificial Intelligence Education Using Text-Based Visual Blocks			score responded that it may be difficult for young students to understand the process of creating an HTML file because they may not be familiar with the concepts of files and folders.
Hasni, A.,Bousadra,F., Belletête,V.,Benabdallah, A., Nicole, M. &Dumais, N (2016)	Trends in research on project-based science and technology teaching and learning at K–12 levels: a systematic review	Secondary data	Data was entered in the Sphinx Lexica software for analysis	Students develop a final product (artefact); the students are engaged in investigations or design activities. There is collaboration among students, teachers and others in the community
(Queiroz et al., 2020)	AI from concrete to abstract: demystifying artificial intelligence to the general public.	Secondary data	Experiment	A visual programming environment that makes use of the WiSARD WANN to enable people to develop systems with some learning capability
Zimmermann-Niefeld et al., 2020	Youth Learning Machine Learning through Building Models of Athletic Moves.	Secondary data	Experiment	An iOS application that supports users in building, testing, evaluating, and using ML models of gestures based on data from wearable sensors
(Kahn & Winters, 2017, 2018; Kahn et al., 2018, 2020)	Deep learning programming by all.	Secondary		Additional blocks to the visual programming language Snap! that provides an easy-to-use interface to both AI cloud services and deep learning functionality
(Druga, 2018)	Growing up with AI: Cognimates: from coding to teaching	Secondary	Experiment	An AI education platform for programming and customizing the development of AI models

Authors	Article Title	Data Collection Method	Data Analysis Approach	Findings
	machines			embodied in devices, such as Amazon's smart speaker Alexa, Cozmo,
(Alturayeif et al., 2020).	DeepScratch: Scratch Programming Language Extension for Deep Learning Education.		Experiment	A programming language extension to Scratch that provides elements to facilitate building and learning about deep learning models by either training a neural network based on built-in datasets or using pre-trained deep learning models

Discussion

Barriers to Machine Learning in K-12

As indicated in Table 1, 5 out of the 17 selected articles take into consideration the barriers of machine learning among K-12 students. These studies are Wagenheim, Jean, Hauck, Pacheco, and Bueno (2020), Sarker, Jamnik, and Spott (2015), Baldwin (2000), Tedre (2017) and Park and Shin (2021). The study by Wagenheim et al. (2020) indicated that the lack of information on how the tools have been developed and evaluated is the major barrier to machine learning. Sarkar, Jamnik, and Spott (2015) identified selection and coordination barriers as the most common of all the barriers the users faced. Again, the study by Baldwin and Kuljis (2000) identified a lack of attention to machine learning as the major barrier. Park and Shin (2021) identified teachers' lack of skills as a barrier. Baldwin and Kuljis (2000) noted programming demands as a hindering block while Marques et al. (2020) noted a lack of support for the training of instructors as a barrier to the use of machine learning.

Key barriers are identified as a lack of information on how the tools have been developed and evaluated (Wagenheim et al., 2020), selection and coordination barriers (Sarkar, Jamnik, and Spott, 2015), lack of attention to ML and programming demands (Baldwin and Kuljis, 2000). The study by Wagenheim et al. (2020) investigated the visual tools that exist for teaching ML in K-12 through the development of custom ML models. The study intended to characterize and compare these tools, to provide an overview to guide their systematic selection as well as to identify potential gaps and opportunities for future research. The study indicated that the lack of information on how the tools have been developed and evaluated, although, the results of few explorative empirical studies (for example, ...indicate the usability and usefulness of these tools in K-12 as barriers.

Also, Sarkar, Jamnik, and Spott (2015) investigated the learning barriers users encountered and which parts of the interface were most useful and why. The study found that selection and coordination barriers are the most common of all the barriers the users faced. Sarkar, Jamnik, and Spott (2015) focused much on the learning barriers of machine learning while Wagenheim et al. (2020) emphasized the lack of support for a performance-based assessment of the created machine learning models. Wagenheim et al. (2020) indicated the problems that come along with the usage of visualization tools unlike Sarkar et al. (2015) and indicated that neither the tools nor the associated educational units provide any kind of embedded or associated support, yet, assessment in the learning process is important to provide feedback to the learner, teacher, and other interested stakeholders. Also, the data for the Sarkar et al, (2015) study was analyzed with Kulesza et al's coding and collected through observation of tasks performed by the participants. Wagenheim et al. (2020) on the other hand obtained the data through digital databases and libraries in the field of computing, including ScienceDirect and Wiley with access via the Capes Port. Again, Wagenheim et al. (2020) used purposive sampling in selecting the participants while Sarkar et al. (2015) used random sampling in selecting the participants. Again, the study by Baldwin and Kuljis (2000) explores the background that will inform such future research experiments that need to be carried out about the learning of programming using visualization techniques. The study concluded that there have been significant issues with the learning of programming and that these issues have not been given due attention in the literature to date. Tedre et al. (2017) also charted the emerging trajectories in educational practice, theory, and technology related to teaching machine learning in K–12 education and concluded that there is no consensus over the trade-offs necessitated by black-boxes, and there is a paucity of research on their effects. Park and Shin (2021) investigated how a variety of big data/artificial intelligence programs using a block-based programming environment and investigated the advantages of K-12 big data intelligence. It was found that teachers who did not give too high a deployability score responded that it may be difficult for young students to understand the process of creating an HTML file because they may not be familiar with the concepts of files and folders. Baldwin and Kuljis (2000) confirmed the findings of Park and Shin (2021) by indicating that Programming demands complex cognitive skills such as reasoning and planning and visual programming uses visual expressions such as diagrams, free-hand sketches, icons, or graphical manipulators. Baldwin and Kuljis (2000) identified learning programming and visual programming as key themes of the study while Park and Shin (2021) identified code complexity. Marques et al. (2020) also indicated that there is a lack of support for the training of instructors to prepare them adequately for the application of ML in the classroom.

Visualization Tools for Teaching ML at K-12

Most of the tools as identified in the search employed gamification in their design and concentrated on ML model development in the form of software and also considered the practice and pedagogies of using visualization tools for teaching machine learning. The studies that considered practice and pedagogies include Wan et al. (2020), Tedre et al. (2017), Dwivedi et al. (2021), and Marques, Wangenheim, and Hauck (2020). Wan et al. (2020) found that the face-overlay metaphor can inform the design of future technologies that support the learning of similarity-based ML methods such as k-nearest neighbor classification, information retrieval, and anomaly detection. Wan et al. (2020) further noted that the Smiley Cluster system can positively support the learning of k-means clustering, which is centered around similarity comparison and global understanding. Tedre et al. (2017) also identified MLflow and NN-SVG as appropriate for supporting Machine Learning in K-12 schools. Similarly, Dwivedi et al. (2020) noted that ML flow is good for Machine Learning in K-12 education. Zimmermann-Niefeld et al., (2019), designed a visualization tool known as AlpacaML aimed at teaching ML at K-2, It is an iOS base application intended to support users in the process of building, testing, and evaluating gesture models with data extracted from wearable sensors. With their bid to introduce visual programming to K-12 learners, (Queiroz et al., 2020), also came out with the BlockWiSARD which is a visual programming environment that uses the WiSARD WANN to help learners develop systems that have some learning capabilities. Cognimates is also a visualized AI education platform used to program and produce customed AI models encapsulated in devices, such as Amazon's smart speaker Alexa, Cozmo, Druga, S (2018). DeepScratch A programming language extension to Scratch that provides elements to facilitate building and learning about deep learning models by either training a neural network based on built-in datasets or using pre-trained deep learning models (Alturayeif et al., 2020). The eCraft2learn tool is also an addition to the visual learning tools which is geared towards providing an easy-to-use interface to both AI cloud services and deep learning functionality (Kahn & Winters, 2017, 2018; Kahn et al., 2018, 2020).

Educational Approach to ML with Mobile Applications is a set of App Inventor extensions covering several ML subfields, among which the Teachable Machine extension allows users to develop an ML model (Zhu, 2019) The Google Teachable Machine (TM) is a web-based interface that allows people to train their own ML classification models, without coding, using their webcam, images, or sound (Carney, 2020) Rodriguez and his team came out with Learning ML: A platform aimed at learning supervised ML for teaching ML in K-12 (Rodríguez-García et al., 2020), the mblock is a block and code-based programming software and it is Teachable Machine extension that allows learners to create an ML model(https://www.mblock.cc). A web-based visual programming environment for Data Science Education designed by Lane also employs visualization to aid the teaching and learning of ML at the K-12 level (Lane, 2018). ML4K is a visual tool that introduces ML by providing practical experience for training ML systems and building models with them (Rao et al., 2018) . The Orange: A data visualization, ML, and data mining toolkit that features a visual programming front-end for exploratory data analysis and interactive data visualization (Demšar,2013). Godec et al., 2019) with their Personal Image Classifier (PIC) allows learners to train, test, and analyze personalized image classification models with an extension, the MIT App Inventor allows using the models in apps and it is Web-based (Tang et al., 2019a, b). RapidMiner also contains a comprehensive data science platform with visual workflow design and full automation of ML solutions (Sakulkueakulsuk et al., 2018) ScratchNodesML is A system enabling children to create personalized gesture recognizers and share them (Agassi et al., 2019). All the above elaborated visualization tools are designed to help learners acquire knowledge and skills in ML in the K-12 settings but there comes a constraint as fewer tools support the integration with text-based languages such as Python. Most of the tools are available online for free, but some require user registration and/or the use of API keys, which may be a bit confusing for the target audience to acquire and use. Most of the tools are also available in English only. Only mblock and ML4K are available in several different languages supporting a wider application, as typically native languages are required at this educational stage (Agassi et al., 2019).

Pedagogy of Machine Learning for K-12 Schools

Two of the studies (Sanusi, 2021; Hasni et al., 2016) focused on the pedagogy of Machine Learning. Sanusi (2021) identified pedagogical frameworks suitable for machine learning in K-12 and these include active learning, inquiry-based, participatory learning, and design-oriented among others as suitable for ML learning in K-12 settings. Hasni et al. (2016) also noted that participatory learning best supports the use of machine learning in schools.

Pedagogies suitable for machine learning for K-12 schools include active learning, inquiry-based, design-oriented (Sanusi, 2021), and participatory learning (Sanusi, 2021; Hasni et al., 2016). Sanusi (2021) in his study explored pedagogies for machine learning in the literature and identified potential pedagogical frameworks suitable for machine learning in K-12. Based on a sound approach, Sanusi (2021) found that learner-centered approaches such as active learning, inquiry-based, participatory learning and design-oriented among others are suitable for M-learning in K-12 settings. However, Sperling and Lickerman (2012) noted that various pedagogical tactics are reported for teaching machine learning in K-12 settings which are active learning, personalized learning, visualization, using real-world applications, customizing to the domain(s) of students, and project-based learning. Hasni et al. (2016) supported the work of Sanusi (2021) by indicating that participatory learning is most suitable for ML.

Conclusions

This section concludes the entire literature review and makes recommendations to improve the use of machine learning in K-12 schools. This paper, through appropriate inclusive and exclusion criteria and a search of the database, relied on 17 studies on machine learning for K-12 schools. The paper has three specific objectives to identify barriers to machine learning, benefits of using machine learning, and pedagogy for machine learning in K-12 schools. Based on these the study concludes that machine learning has several barriers, with major ones as lack of information on how the tools have been developed and evaluated, selection and coordination barriers, lack of attention on ML by educational stakeholders, and programming demands. However, despite these barriers, machine learning offers some educational benefits with major benefits such as visualization and experimentation, which are critical for teaching and learning at K-12 schools. Lastly, every tool has its appropriate pedagogy and so is machine learning in K-12. The most appropriate pedagogy for machine learning is participatory learning, though others like active learning, inquiry-based and design-oriented are also recommendable.

Recommendations

This paper makes the following recommendations;

1. For an effective use of machine learning to enhance visualization and experimentation in K-12 schools, stakeholders, particularly, teachers need to acquire appropriate and specific information and technical know-how or skills about machine learning.
2. All teachers should be sensitized to adopt participatory learning pedagogy to enhance the effective use of machine learning in K-12 schools.
3. Machine learning should be integrated into teaching and learning in K-12 schools since it is ideal for visualization and experimentation, which are inevitable for effective teaching and learning in K-12 schools.

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Author Information

Adjei Amaniampong
https://orcid.org/0000-0003-1025-3215
Lecturer
Offinso College of Education
Ghana
Department of Mathematics/ICT
Technical University of Dresden
Germany
Contact e-mail: *adjei.amaniampong@tu-dresden.de*

Solomon Oyelere
https://orcid.org/0000-0001-9895-6796
Professor
Department of Computer Science
Lulea University
Sweden