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Machine Learning Skills To K–12

Amira Bibo Sallow[1], Renas Rajab Asaad[2]*, Hawar Bahzad Ahmad[2], Saman Mohammed Abdulrahman[2], Ahmed Alaa Hani[1], Subhi R. M. Zeebaree[3]

[1] *Department of Information Technology, Duhok Technical College, Duhok Polytechnic University, Duhok, KRG, IRAQ*
[2] *Department of Computer Science, College of Science, Nawroz University, Duhok, KRG, IRAQ*
[3] *Energy Engineering Department, Technical College of Engineering, Duhok Polytechnic University, Duhok, KRG, IRAQ*

*Corresponding Author: eman.khorsheed@nawroz.edu.krd
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Abstract

The promise of data-driven methodology in various computer disciplines has been shown by the many real-world implementations of methods based on machine learning (ML) over the last couple of decades. ML is finding its way into the computer curriculum in higher education, and an increasing number of organizations are introducing it into computer education in grades K–12. Researching how agency and intuition grow in these situations is critical as computational learning becomes increasingly common in K–12 computer instruction. However, knowing the difficulties associated with teaching algorithmic learning through grades K–12 presents an even more difficult barrier for computer education research, given the difficulties educators and schools now face in integrating traditional learning. This article describes the prospects in data mining schooling for grades K–12. These developments include adjustments to philosophy, technology, and practice. The research addresses several distinctions that K–12 computer educators should consider while addressing this problem and places the current results into the broader context of computing education. The research focuses on crucial elements of the fundamental change needed to properly incorporate ML into more comprehensive K–12 computer courses. Giving up on the idea that rule-based, "traditional" programming is necessary for next-generation computational thinking is a crucial first step.

1. Introduction

Early educators were aware of shifts in the work economy. They were the first to acknowledge that everyone needed to be aware of the latest technological advancements, which they believed would fundamentally alter society and the workplace [1]. Guzdial asserts that computer and software education proponents for students in grades kindergarten through twelve have offered various justifications for their efforts. Proponents said that comprehension of computer fundamentals was required to appreciate the one-state record-keeping of the algorithm-driven virtual and physical worlds [2]. The new technique was being used by scientists for population studies and large-scale computing more and more. Understanding these ideas also helps individuals better use technologies and consider algorithms' significant impact on their lives. They contend further that learning math, science, solving problems, and life in general may be facilitated by computers. Workplace computing is becoming more and more important. It has recently become a crucial skill strongly associated with industrial innovation

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and economic success. The advantages of increased business efficiency and the transfer of computing power from a small number of people to a large number have led to a steady increase in the levels of abstraction of programming [3, 4].

Computer power connectors have been quickly shifting away from the hardware since the 1950s, and every ten years, new educational initiatives are developed to distill the most important automation strategies of the previous century [5]. Computer experts usually agree that one has to be familiar with at least one abstraction level lower than the one they are currently working at since the degree of abstraction in computing across all educational levels has steadily risen. It was argued in the 1950s that a rudimentary understanding of electronics benefited professionals in the computer business [6]. Then, it was claimed that knowing octal machine code benefited programmers using assembly language. Assembly language knowledge was deemed necessary until it was determined how it was used in more advanced languages like Pascal, C, C++, and Java. Developing methods and data structures will be helpful for users of exceptionally effective class libraries [7].

The topic of this article, which focuses on a specific phase of this evolution, is how proficiency in high-level or traditional" programming affects the uptake of artificial intelligence (AI) and machine learning (ML) theoretical toolboxes and languages [8, 9]. The scope and aim of computer education initiatives have constantly changed to keep up with technological innovations. Since the advent of contemporary computers, a greater variety of kids at younger ages have been taught using instructional methodologies (Figure 1). They were first used in 1960s high schools and are now used in kindergarten and elementary education. Alan Perlis bemoaned in 1960 that everyone would eventually need to learn program and "algorithmizing" since there was a dearth of instruction in this area.

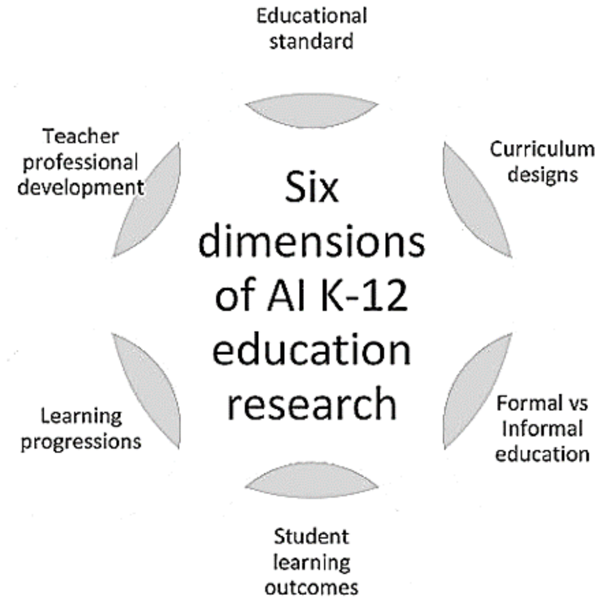

Fig. 1 *Application of k-12 System [10]*

A few US high schools began using DEC PDP-8 minicomputers in the middle of the 1960s; in 1965, the Small Man Artificially project started teaching kids machine languages; in 1967, the kid-friendly programming platform Logo was introduced; and in 1968, the kids' small machines The Dynabook made its debut [11].

The article will cover the integration of machine learning (ML) skills into the K–12 education system. It will discuss the importance of early exposure to ML concepts, the benefits of incorporating these skills into the curriculum, and practical methods for implementation. The article will explore current efforts and case studies detailing how schools can effectively teach ML to students of various age groups and academic levels. Additionally, it will address the necessary resources, training for educators, and the role of technology in facilitating this learning.

1. Highlight the importance: emphasize why teaching machine learning skills at the K–12 level is crucial for future job markets and technological literacy.
2. Identify benefits: outline the advantages for students, including improved problem-solving skills, creativity, and understanding of technology.
3. Provide implementation strategies: offer practical advice and methods for integrating ML into the existing curriculum, including resources and tools.
4. Case studies and examples: present real-world examples of schools or programs successfully teaching ML to K–12 students.

J. of Soft Computing and Data Mining Vol. 5 No. 1 (2024) p. 132-141

5. Address challenges: discuss the potential obstacles in implementing ML education at this level and propose solutions.
6. Support educators: guide training and resources for educators to teach ML concepts effectively.

The rapid advancement of technology and the increasing importance of machine learning in various industries have created a gap in the current education system. Most K–12 curricula do not adequately prepare students for a future where ML skills are essential. This lack of early education in ML results in a workforce that may be unprepared for the demands of future job markets. Moreover, without exposure to ML concepts from a young age, students may miss out on developing critical thinking and problem-solving skills nurtured through understanding and working with these technologies. The article will address this gap and propose solutions to effectively incorporate ML education into K–12 systems.

2. Literature Review

Another significant technical change occurred in the computer environment in the last ten years. A range of data-driven techniques for ML has joined standard programming, such as rule-based good outdated simulated intelligence, which has been the main driver of automation for the last 70 years [12]. The secondary machine age that has received much attention is predicated on methods' capacity to automate a wide range of activities that are difficult for conventional, rule-based programming [13]. Obtaining big enough data sets using learning algorithms is far less complex for vast issues than establishing the rules required for rule-based software, as shown by several application fields. Neural networks and conventional software provide the foundation of many well-known examples of the most recent advancements in automation. Examples include face recognition, self-driving cars, computer-based tumor diagnostics, and the game Go, in which a computer was trained to become superhumanly competent by learning everything independently [14]. Many examples of job losses primarily not associated with traditional rule-based program development are cited in reports of the recent, much-feared loss of jobs to information technology in the knowledge work domain. Instead, these job losses are associated with areas where the task structure became amenable to contemporary ML's sophisticated optimizing and mathematical methods [15-22].

Algorithm:

The rapid advancement of technology has made machine learning (ML) an integral part of our everyday lives, influencing industries from healthcare to entertainment [22]. As we prepare the next generation for a future driven by data and artificial intelligence, it becomes essential to integrate ML concepts into K-12 computing education. This guide outlines a systematic approach to embedding ML into the curriculum, ensuring that students not only understand the theoretical aspects of ML but also gain hands-on experience and critical thinking skills necessary for the future.

Our approach begins with defining clear learning objectives and curriculum goals, ensuring that the integration of ML is purposeful and aligned with educational standards. By developing age-appropriate materials, designing interactive activities, and providing professional development for educators, we aim to make ML accessible and engaging for students of all ages. Additionally, this guide addresses ethical considerations, evaluates the effectiveness of ML instruction, and identifies potential challenges, ensuring a holistic and sustainable implementation.

Collaborating with industry partners and researchers, we stay updated on the latest advancements in ML education, documenting best practices and lessons learned to guide future initiatives. Following these steps can equip students with the skills and knowledge needed to thrive in a rapidly evolving technological landscape [23].

Step 1: Define learning objectives and curriculum goals for integrating ML into K-12 computing education.
Step 2: Develop age-appropriate educational materials and resources for teaching ML concepts.
Step 3: Design interactive activities and projects to engage students in hands-on ML experimentation.
Step 4: Provide professional development opportunities for educators to build expertise in teaching ML.
Step 5: Adapt ML concepts to align with existing K-12 computing standards and frameworks.
Step 6: Address ethical considerations and societal implications of ML technologies in educational contexts.
Step 7: Evaluate the effectiveness of ML instruction through student assessments and feedback.
Step 8: Identify potential challenges and barriers to teaching ML in K-12 settings.
Step 9: Collaborate with industry partners and researchers to stay updated on advancements in ML education.
Step 10: Document best practices and lessons learned to guide future ML implementation in K-12 computing education.

However, some differences exist between teaching rule-based arithmetic, computational thinking, or classical computers in K–12 and teaching data mining (DM). This article aims to clarify the rationale behind the growing consensus that ML instruction will represent the next frontier in computer education research. The paper outlines important pedagogical and technical components of computer education that should be reexamined, along with their implications for instructional design, in light of the growing use of ML methods in K–12 education. K–12 computer instructors who want to include ML software more in their classes are the target demographic for this article. Although K–12 ML projects differ from one another, this article has highlighted a few of their similarities. Understanding these techniques creates a foundation that is essential for future educational innovations.

3. Proposed Methodology

The conclusion that typical systematic reviews are inappropriate for the task of studying computational learning in K–12 has been reached for three reasons: 1) The topic's novelty, 2) The absence of a common vocabulary, and 3) The range of scholarly viewpoints represented in the body of currently available, peer-reviewed research on AI education.

These studies demonstrate that exploratory literature reviews outperform standard literature reviews in locating relevant material. This study and the other reviews used the exploratory studies structure, which tries to map a developing topic quickly by identifying its key ideas and their linkages, noteworthy results, and research needs, among other things (figure 2). Scoping reviews are beneficial for mapping areas with a wide range of jargon, like ML teaching in K–12, since they do not depend on predefined search words to discover relevant research, unlike typical systematic reviews. Scoping reviews have reduced replicability and two limitations: statistical summaries of outcomes and the capacity to evaluate the caliber of the study found. Alternatively, they can provide a narrative interpretation and overview of the earlier studies.

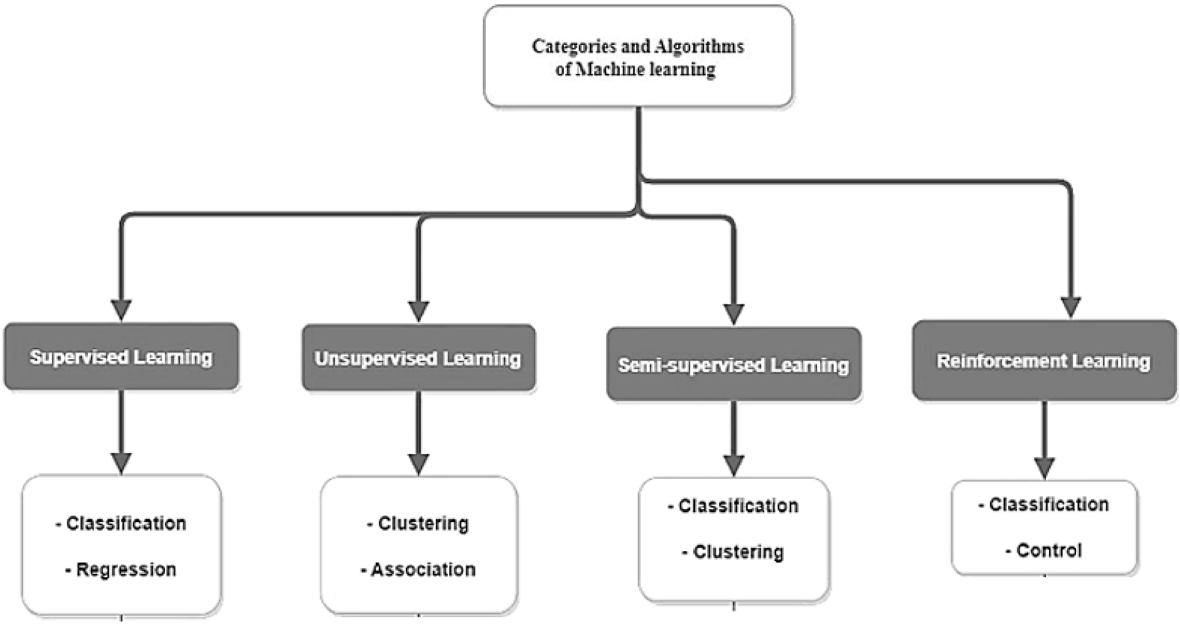

Fig. 2 *Classification of the system [24]*

This research initially employed keyword sets taken from and performed many searches over the ACM Digital Libraries, IEEExplore, the database maintained by Scopus, and Google Scholar to find the literature on the subject. From each of the generated sets, whose sizes varied from zero to 62.200, an upper limit of 100 abstracts was selected to locate research on the use of AI for K–12 education. Secondly, snowball sampling was applied to the bibliography parts of the previously acknowledged publications to expand the field overview.

4. Machine Learning Education in K-12

Since the field's inception in 1956, artificial intelligence (AI) theory and application have been essential elements of computer-based higher education [25]. These days, a large portion of AI theory instruction in higher education is on the mathematical underpinnings of the algorithms required to create models that can forecast or generalize utilizing unstructured data (figure 3). Moreover, a great deal of practical education in artificial intelligence concentrates more on modeling purposes, algorithms, and tool deployment than on elucidating the underlying algorithms' structures and teaching students how to master them to the fullest extent possible [26-28].

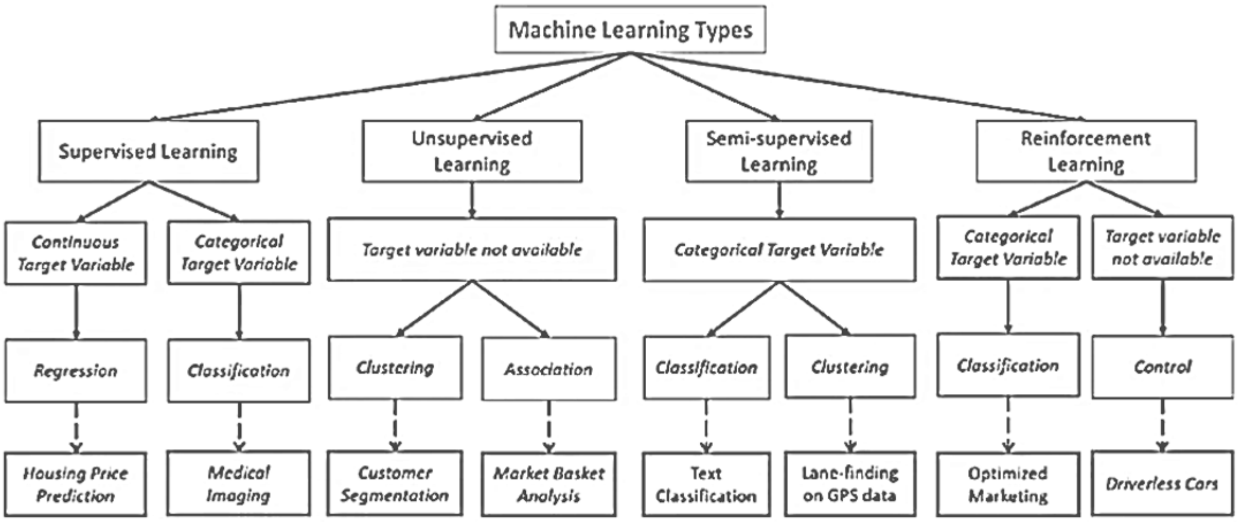

Fig. 3 *Architecture of the system [29]*

Historically, the majority of AI-related activities in K–12 education have fallen into one of three categories [30]:

- AI-based tools to enhance learning;
- AI-based instruments to explore learning processes; and
- AI will help with administrative duties in schools.

Numerous research projects have tried to automate learning scenario components such as the student, teacher, subject matter, environment for learning, and learning objects. Some approaches include adaptive classrooms, pedagogic agents, automated governance, and intelligent tutoring systems. Views on the fusion of AI and education have evolved along with technology and methods of instruction [31-34].

Many ML efforts rely heavily on pedagogical and curriculum approaches. One group developed ideas for a constructionist AI curriculum for grades K–9. It was created with the help of the Droodle creative game, AI ethics, and the PopBots robot tools. A list of 17 skills and 15 design characteristics for a focused-on-students AI program is provided by a recent study that summarizes the research on AI [35-37].

5. Characterizes K–12 ML Education

Teachers may now include AI as a fundamental part of ML programs, thanks to SO-CALLED "LOW-FLOOR" approaches that are progressing and commodifying ML training [38]. Currently, ML-based techniques are often used in user interfaces. The ongoing refinement of interfaces to train ML models might result in end-user programming becoming increasingly oriented toward data-driven applications. In recent years, a large body of research has been conducted on teaching computational intelligence at various educational levels. This research offers specific indicators of how higher education is changing. A summary of some of these modifications may be found in this section [39].

- Broader classes of example applications become accessible for different K–12 education levels: Similar to how ML has made it possible for tasks to be automated in the market, ML is opening up new possibilities for computer examples in the classroom. Consider media use, which has been included in computer instruction for a long time: Research on using pictures, movies, and music to instruct computers has a long history [40]. ML provides a plethora of quick, real-world uses in K–12 education since it excels in media-related application domains, such as video, photos, sensors, and sound. Anything that facilitates the collection of large amounts of data can teach us a lot about ML. The pedagogical benefit of co-design stems from the fact that students, while collaborating to create ML models, test them, or co-develop their functionalities, also share their evolving ideas and understandings and build a complex set of personally meaningful relations in abstraction or the real-world problem-solving environments at hand [41].
- Focus shifts from rules to data: Students may create ML models rather than only relying on hand-coded commands that an algorithm would execute given various inputs since many ML (machine intelligence) projects supply the system with much data to learn from [42]. Data from sensors, gestures, online searches, cartoon images of youngsters, and made-up information about them have all been utilized in studies, as shown in Figure 4. Other data sources include poses, drawings, audio, and video. Because of

this, knowing how to produce, organize, clean, label, etc., give the classroom teaching data is the primary learning goal of many ML algorithms in computer education [43].

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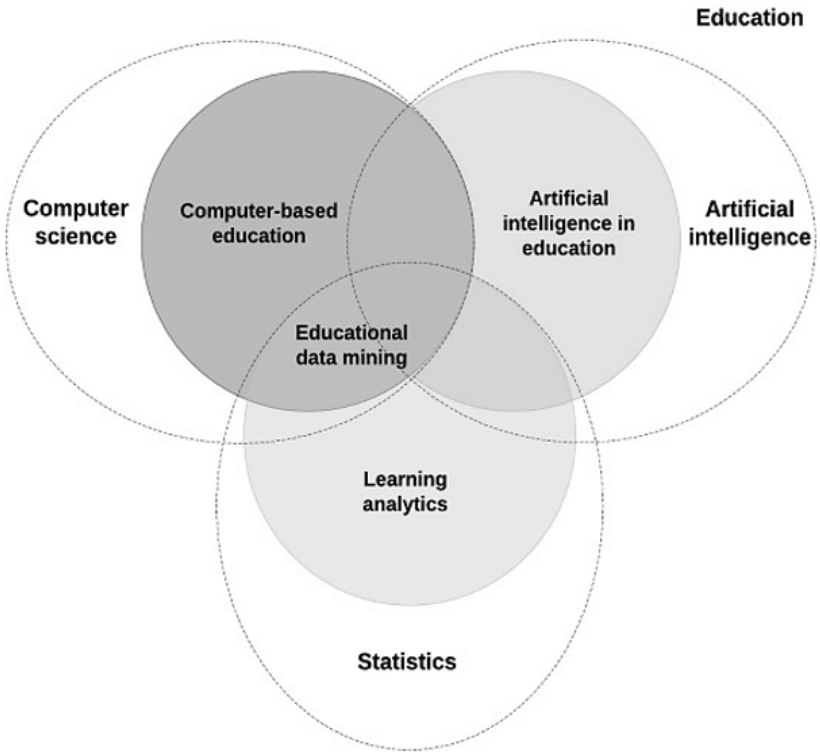

Fig. 4 *Implementation of the system [48]*

- The notional machines evoked in ML differ greatly from those of traditional programming: According to Sorva, a major area of study in computer education has been how to help students get a solid conceptual understanding of a fictional system. Nothing about ML can be learned from much research on fictional machines involving both amateurs and specialists [44]. A little study has been done on the former in the corpus of computer education literature. Still, it is obvious that the mental models of notional systems used in computing companies for ML will be quite different from those used in conventional programming instruction [45, 46].
- ML systems are tested and debugged differently from rule-based programs: There hasn't been sufficient research on K–12 computer education debugging techniques to inform ML education programs that let students train their accord models. This is because "debugging" data mining models differ greatly from conventional rule-based approaches. Rather than being strictly discrete, many ML algorithms provide "soft" outputs that indicate the likelihood that the data being utilized will fall into various classes [47-49].

However, training black-boxed artificial intelligence models ultimately relies on identifying the ideal feature set or hyperparameter via trial and error. Different iterations of "data gathering data entry, visualization of information, developing features, creating develops, testing models, and data authorization," depending on the model (as shown in Table 1), have been used to educate the ML operations explicitly.

Table 1 *System application potential and pitfalls implementation for the system*

Potential	Pitfalls
Increased computational thinking skills: Students learn to break down problems, analyze data, and make predictions	Overemphasis on algorithms and tools: Students may focus on using pre-built tools without understanding the underlying concepts
Enhanced problem-solving skills: Students apply ML techniques to real-world problems, fostering creativity and innovation.	Lack of ethical considerations: Students may not understand ML models' potential biases and limitations.
Demystifying AI and technology: Students gain a deeper understanding of how ML works, fostering	Limited access to technology and resources: Not all schools may have the necessary hardware and

responsible use and critical thinking.	software. Teacher training to implement effectively.
Preparation for future careers: Students develop skills relevant to data science, computer science, and engineering.	Unrealistic expectations: Students may overestimate the capabilities of ML and its potential impact on society.
Engaging and interactive learning: ML projects can be fun and motivating, promoting interest in STEM fields.	Overlooking foundational skills: ML should complement, not replace. Core programming and mathematical skills.
Promoting inclusivity and equity: ML can be used to address social and environmental challenges, fostering a sense of purpose.	Potential for bias in data and algorithms: Students need to be aware of and address potential biases in ML systems.

6. Discussion

Artificial provides a different perspective on computations and automation than the rule-based computer and programming-based digital understanding. However, it addresses several topics that programming endeavors cannot get to. There are a number of drawbacks, dangers, and risks related to ML in elementary through high school that have been researched. First of all, the actual children learning processes, not as the ML learning processes algorithms, the teaching may be cursory and narrow, especially in fewer levels of education as well as in "low threshold" use. The procedures are described differently in each endeavor. A certain project, for example, described its workflow as the process of feature, gathering entry of data, data visualization, model building, evaluations, and data authorization. A different individual says that requirement evaluation, training data collection, testing, and model deployment are all involved for the model to function in use. In some places, the procedure might be additionally black-boxed: In one study, the remaining parts of the process were hidden, and the focus was merely on labeling and evaluating information. The challenge with Learning Rate (Lr) for K–12 is simplifying ML without resorting to complicated arithmetic.

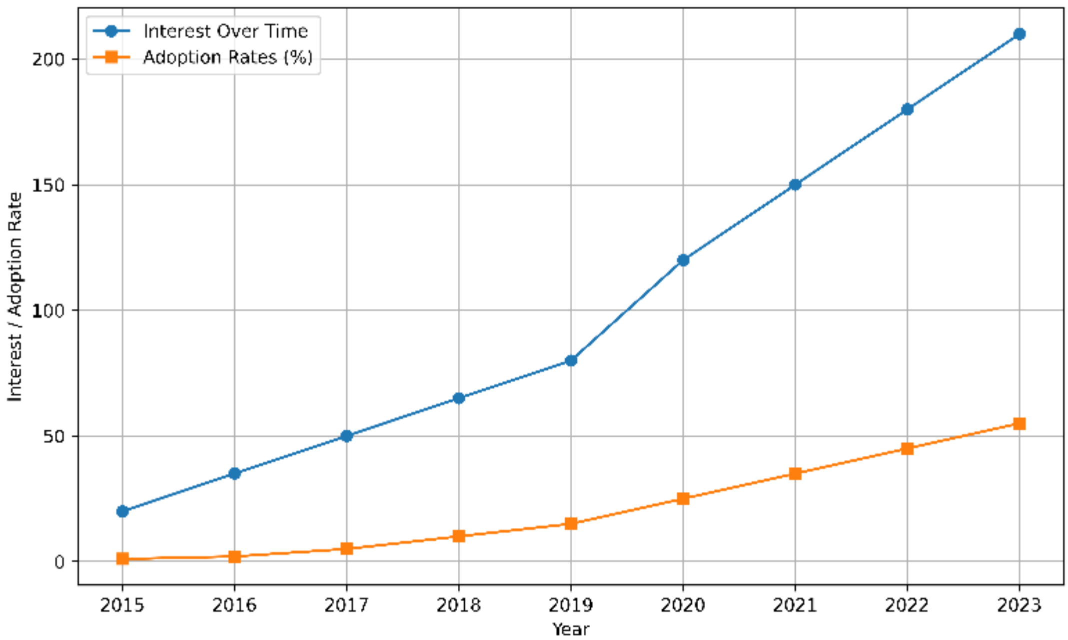

Fig. 5 *Teaching ML In K-12 computing education for the system application*

It is not appropriate to reiterate the unrealistic aspirations for Symbol that were ultimately crushed when the project failed to live up to projections in ML instruction for students in grades K–12. Although data science (also known as it makes it possible to automate formerly job lessons, its possible uses are currently quite limited, and most of the press media's hype around Lr is unfounded. A fundamental worry in algorithmic teaching revolves around the "her result," when a system seems to others to be smarter than its basic functioning warrants black boards further obscure operating.

7. Conclusion

The limits of what may be learned about computers have gradually changed across computing's disciplinary history. Incorporating modern technology into studying computers has always been advantageous since it allows for better interfaces and stacks of levels of abstraction that conceal underlying complexity. Computer educators have predicted a K–12 computer education change as ML permeates daily technological and technological literacy. Furthermore, ML applications are extensively used. Research on deep learning training in K–12 schools is growing, and it differs greatly from conventional computer curricula that strongly emphasize scripting and cognitive reasoning in many areas. However, as educational institutions and instructors strive to keep up with the rising trend of incorporating computational thinking into the curriculum, teaching ML to students between the ages is getting more and more difficult. Surprisingly, little study has been done on how individuals learn to teach, assess, modify, and implement ML systems in the corpus of works on computer education. Most research in ML education is either analytical (concept extension, essays, curriculum designs) or empirical (exploratory, proof-of, or Marco Polo-type types). However, despite these difficulties, it is essential to comprehend how ML-based systems rely on a function in people's daily lives. Because of this, developing ML education necessitates beginning from scratch. Research is required on all other aspects of education, including pedagogical models, domain integration, skill progression systems, ethical quandaries, and suitable instructional technologies. This article describes how computer teachers should think about the pedagogical features of methods for learning in K–12 classrooms. If future generations are to influence the systems surrounding them, computer research into education has to focus on this much more.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

All authors have contributed significantly to the research and writing of this paper, each bringing their unique expertise and insights to ensure the quality and comprehensiveness of the final manuscript.

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