Identification of learning styles using an enhanced Machine learning algorithm: A systematic Literature review

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Abstract

Recently, advanced machine learning (ML) algorithms have revolutionized the way to comprehend learning patterns and their idiosyncrasies towards specific learning styles. In light of this phenomenon, through a systematic literature review process, we are here to consolidate and scrutinize all relevant research contributions accumulated so far regarding enhanced ML algorithms developed to identify and personalize learning scenarios based on various learning styles. The review is mainly focused on methods of the current study, impression of almost continuous algorithmic advancement in the field, and their respective outcomes to adjust learning content and strategies through ML techniques to reform the learning.

1. Introduction

This paper offers a brief overview of learning styles and personalization of educational settings using them. It justifies need of the Artificial Intelligence and Machine Learning (AI/ML) algorithms to ease up, support, and follow learning styles in 21st century educational environments. The contribution of research is directed towards this. Current learning wherever is mostly personalized. It is either facilitated by AI or generated from ML agents. This kind of learning may depend on several knowledge attributes and learning styles of various subjects and domain areas. Knowledge points are used to enforce, test, and pass out knowledge. Hence, it does not depend on D() more but it does depend on the smart agents and users. For example, it adjusts and personalizes different learning scenarios based on the learning styles of the students, providing information that is more tailored making it more engaging and effective e-learning. As a step forward, the next generation of learners and the internet (Fox and MacKeogh, 2011; Brusilovsky and Henze, 2007) need more individualized learning paths. This intelligent learning environment is being created through the identification of the learning styles of the learner. Conventional descriptive modes of assessments show the learning styles with a measure of observed and self-reported indicators (Moreno, 2010; Daley et al., 2010). Thus, there is a need to determine the learning styles using techniques and algorithms. Where current approaches include the use of questionnaires, observational methods, and interviews to determine the learning style of students, adding machine learning (\(ML\)) in these conventional analysis methods can induce the more optimal learning styles and enhance student performance. With the ability to process large data sets and recognize patterns in real-time, ML provides a robust way of analyzing learning styles. The recent surge of ML articles in the last several years has made it challenging to identify key studies that have influenced or contributed to the growth in this area. The overall objective of the survey is to cover all the works composed in the field of identifying the learning styles possibilities using the enhanced algorithms of machine learning. Integrating this existing awareness and useful findings of this research and knowledge can become a resourceful tool for the contemporary as well as future scholars. Understanding the learning dynamics can facilitate the development of an efficient and interactive environment for the learners. At the moment, the traditional understanding of the learners into the typical formal learning domain is done through questionnaires and other non programmable conventional methods which may not persist, orderly, and may also become obsolete. On the contrary, as the machine learning technique is relatively very generalized and efficient, learning preferences or behavioral analysis becomes very apparent and instrumental.

1.1 Theoretical background

The dominant learning style and learning style models have remained the cornerstone of educational psychology. There are several different models of learning styles, such as Kolb's experiential learning theory, which identified students as convergers, divergers, assimilators, and adaptors. Also VARK, which is the model of identifying learnera as visual, auditory, reading-writing, and kinaesthetic. A major drawback of all the models of learning styles is that they give us a mental and cognitive explanation for how an individual prefers learning. Conventional ways to discover learning styles Conventional ways of discovering learning preferences identification is through students' self-report answers from questionnaires and also through teachers' observations. While self-report questionnaires or assessments and teachers' observations would be valuable, they are also subjective, highly qualitative, and do not encapture the varied nature of learning styles of long term.

1.2 Application of machine learning in learning style identification

Machine Learning in Education It is important to note that the use of machine learning in education development is just one step forward compared to other machine learning applications. As machine learning is able to directly extract patterns from vast quantities of data, and discern complex patterns in data. Machine learning has the capability to learn from data on how to understand learning preferences. Let us now look at the major machine learning methods in use in educational field which include clustering, classification and recommendation algorithms.

Hasibuan et al. (2023) , presents a model for learning material recommendation using machine learning. The novelty according to the authors was that they postulated a model to improve the quality of educational content by considering student preferences. They showed that by the end of the study, the machine learning model to perfectly determine what students wanted.

1.3 Enhanced learning algorithms

Emphasis on more advanced algorithms. The algorithms have also benefited from superior algorithms; advanced algorithms mitigated many limitations associated with the identification of learning styles in traditional ML models. For example, Li et al. (2023) have proposed BlobCUT, a contrastive learning method suitable for medical imaging, but we find that it can also be used to discover learning regularities in! educational data by eliminating weak representation and learning style. - comparative analysis. The achieved developments are similar to the ones brought by advanced modeling. The more sophisticated machine learning algorithms rely more on deep architectures, known as deep learning or ensemble learning. Troussas et al. (2023) has improved Personalized Learning Resource predictions using Artificial Neural. Their new models achieve better predicting performance than their traditional model.

2. Methodology

In the following subsections, we report: the search criteria that we used for literature (with keywords like “learning styles” and “machine learning”), the data sources (journals, databases) that we used for performing our search and the timeframe that we considered for the articles. The literature search was conducted from January 2021 to April 2021.

3.1 Search criteria

We employed a systematic approach to extract relevant studies from multiple databases such as Scopus, IEEE Xplore and ACM Digital Library. We used the keywords like “machine learning”, “learning styles”, “personalized learning”, “adaptive learning systems” and “educational data mining” in the search field of these libraries. The inclusion and exclusion criteria: The inclusion and exclusion criteria play an important role in choosing relevant articles for scoping study. We specified the criteria that the studies must specifically focus on learning styles and machine learning algorithms.

The keywords used in this paper are ("machine learning" or "artificial intelligence") and ("learning styles" or "learning modes") and ("e-learning" or "online learning") and ("machine learning algorithms" or "intelligent algorithms"). The process started with the identification phase and a total of 6234 records were obtained from six databases, including Scopus (2174 records), ProQuest (1675 records), Web of Science (1263 records), IEEE (466 records), ACM (210 records) ScienceDirect (446 ScienceDirect (446 records).

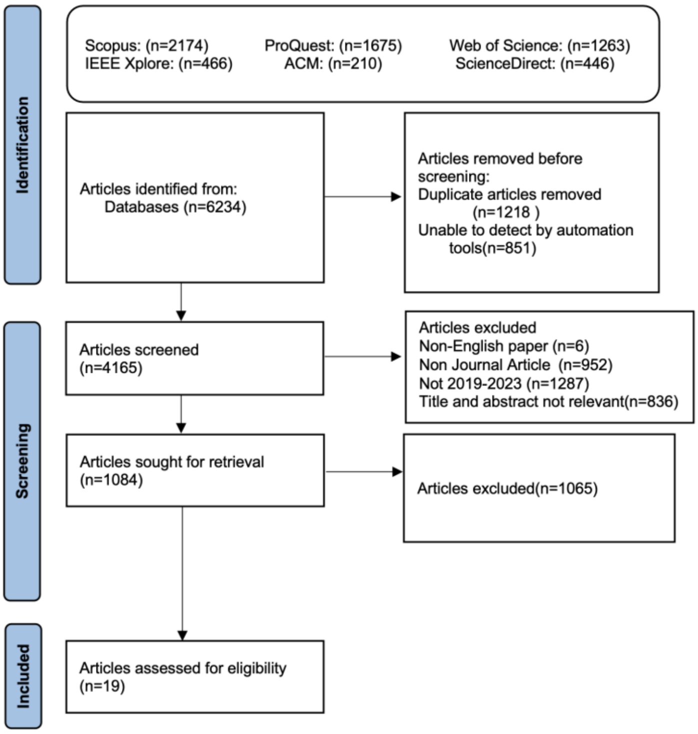

Figure 1 PRISMA

3.2 Data analysis

Looking at Figure 2, it illustrates the total number of occurrences of the search terms over years 2019-2024. Within the figure, each line represents the trend in the number of occurrences over time. As you can see from the Figure 2:

MODEL (orange) has a very high number of occurrences and is increasing at the fastest rate to 2024. It starts with virtually zero in 2019 and has over 60 occurrences by 2024.

PERFORMANCE (green) has a more stable growth pattern, starting with virtually zero in 2019 and has about 45 occurrences by 2024.

RECOGNITION (blue) has a fairly stable increasing pattern, but is a little bit slower than PERFORMANCE.

IMPACT (pink) is clearly increasing from 2020, with about 40 occurrences by

2024.

PREDICTION (light green) and STYLE (purple) both have a similar growth trend, with just over a cumulative total of around 35 by 2024.

CLASSIFICATION (yellow) is increasing, but at quite a slow rate, but generally upwards.

SYSTEM (brown) and STYLES (dark purple) seem to also be relatively slow to increase, but increasing consistently.

BEHAVIOR (red) is the slowest growing, with a low cumulative number of occurrences.

Summarizing, we have seen that all the terms are increasing in total occurrences, with the term MODEL increasing the most, with a high number of occurrences.

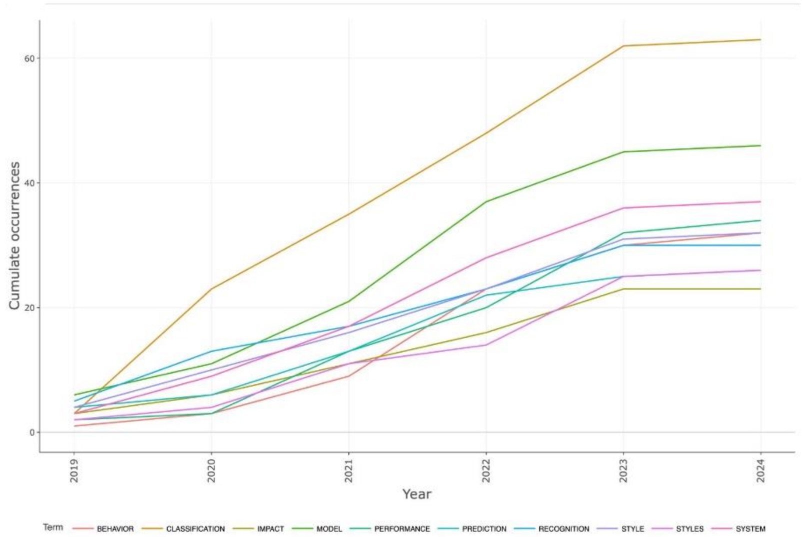

Figure 2 Words' Frequency over Time

This figure 3 presents the term co-occurrence relationships with their thematic distribution. The term located in the center (for example CLASSIFICATION) is linked to much clusters. The clusters are distinguished from the different colors, health is purple thanks to Image and Network, machine learning is green thanks to Model and Performance, health and lifestyle is red thanks to Risk and Life-style. Besides, information in the same cluster appears more frequently, because the big node connects with more terms.

CLASSIFICATION: Located in the middle, it is the biggest node indicating that it has high degree and co-occurrence with more terms.

MODEL and PERFORMANCE: Located next to class, co-occur many times. It belongs to the green cluster representing machine learning and modelling.

RISK and LIFE-STYLE: The red cluster represents health and lifestyle. More co-occurrence means that it can be connected with more terms.

STYLE: Located below the left, the blue cluster. There are co-occurrences with other terms, such as personality and neural network.

RECOGNITION and PREDICTION: Located in the green cluster with Model, it is important among the machine learning and recognition related systems.

IMPACT: Located in the graph's center. It not only belongs to the inter-domain red cluster, but also connects other different themes, so it has many abilities.

DIAGNOSIS: Located in the red cluster, indicating that it belongs to health and lifestyle.

NETWORK and IMAGES: Located in the upper right, deep in purple, indicating that it belongs to the theme of Image Processing and Networking and belongs to the inter-field.

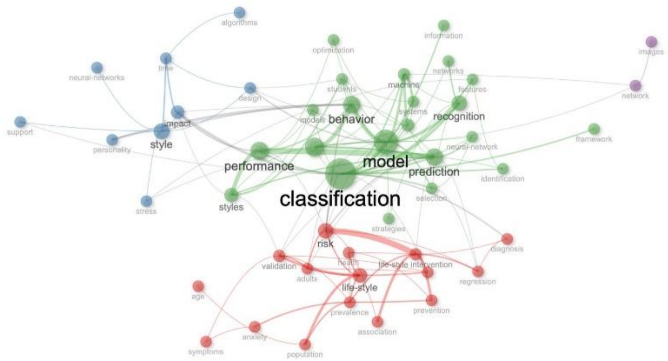

Figure 3 Co-occurrence Network

Figure 4: Factor analysis: Term plot, showing the factors (y-axis and x-axis). Terms are in theme space. Each point in the plane represents a term. This point's position (consisting of its coordinates in the two s directions) reflects the value of the term on the two s. The coordinates of the point are the client's loadings on these factors; such that variables are "close" e.g. Bioinformatics, Modeling, Clusters, Background, Students, Alleviation, Classification, Efficiency etc,. The horizontal axis (Dim 1), which accounted for 41.02% of the variance, separates terms from mental health from terms of health and lifestyle in relation to machine learning and modeling. The vertical axis (Dim 2), which explains 18.52% of variance, mainly distinguishes terms from mental health, thus giving an overview of main terms.

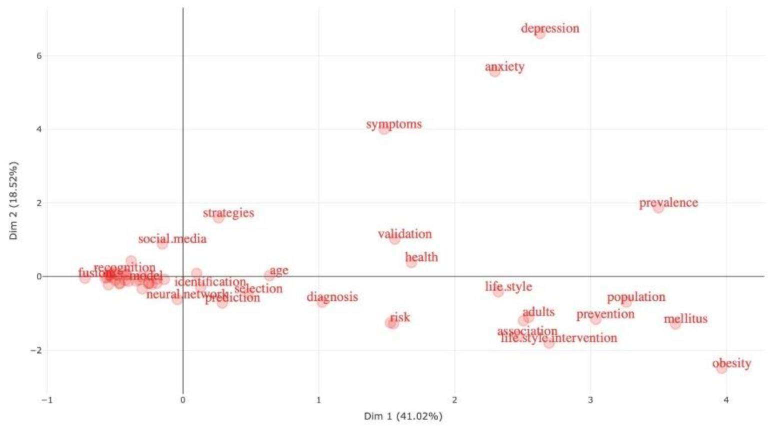

Figure 4 Factorial Analysis

This word cloud map (Figure 5) shows the main research terms in the field of data science are classification, model, recognition, system, performance, prediction, highlighting behavior, health, style, neural networks, the algorithm and other related concepts, while also mentioning specific application areas such as life-style intervention, prevention, students, and diagnosis.

Figure 5 Word Cloud

3.3 Log table

In order to achieve the goal of a complete record of the research process, we have listed the log form (Figure 6). The log form helps to document our research activities, findings, and decisions at every step of the way, thus ensuring that the process of data collection and writing of the literature review is transparently informed.

Date	Task	Detail	PIC
30/4 - 1/5	Determining group information	1. Determination of group size : 2 2. Determination of group leader and members :ADEYEMO SARAFA OLASUNKANMI(leader), CAI FUYUAN, LU RUIQI 3. Create the Whatsapp Group For Further Discussion : "Group 5 SLR"	ALL
1/5 - 18/5	Determine the title and start collecting literature	1. Determine the title of the article : Identification of learning styles using an enhanced Machine learning algorithm in e-learning platform 2. List keywords : Machine learning, Learning styles, E-learning, Machine learning Algorithm, etc 3. Number of databases identified : at least 5	ALL
18/5 - 4/6	Modification of the title and briefly report	1. Determine the final title : Identification of learning styles using an enhanced Machine learning algorithm: A systematic Literature review 2. Brief reporting process: literature collection	ALL
4/6 - 11/6	Identify search terms and start prisma production	1. Identify search terms : ("Machine learning" OR "Artificial intelligence") AND ("Learning styles" OR "Learning modalities") AND ("E-learning" OR "Online learning") AND ("Machine learning Algorithm" OR "Intelligent algorithm") 2. Prisma : preliminary	ALL
11/6 - 17/6	Identify a research question and begin screening articles	3. What are the Research Questions: RQ 1: What are the existing solutions to the problem of identifying learning styles? RQ 2: How do the different solutions found by addressing RQ1 compare to each other with respect to constraints, methods, and/or approaches? RQ 3: What is the strength of the evidence in support of the different solutions?	ALL
17/6 - 7/7	Screening articles and completing prisma	1. Inclusion Criteria : Journal articles, published 2019 - 2023, written in english 2. Databases : Science Direct, Scopus, IEEE Explore, ACM, PopCite, Web of Science, ProQuest	Cai and Lu
7/7 - 20/7	Writing the SLR	Abstract	Cai
		1. Introduction	Cai
		2. Methodology	Cai and Lu
		3. Analysis and discussion	Cai and Lu
		4. Related Literature Review	Lu
		5. Conclusions	Lu
		References	Cai
20/7 - 25/7	Revise and perfect	1. Checkweighing 2.Supplementary to the second revision	ALL

Figure 6 Log table

3. Analysis and discussion

This section reviews the existing related work to analyze the status of application and development of machine learning algorithms in learning style identification. Generally, some important observations from such research works are as follows:

Learning personalization and adaptation: Many works have made progress on personalized and adaptive learning systems. Based on machine learning algorithms, learning styles are used to match course contents with learning proclivities of students. Usually, this personalization is achieved through different machine learning techniques such as contrastive learning, deep learning, and neural networks.

Hybrid methods: A mix of different machine learning algorithms is emerging as a promising concept as it combines varied algorithms to produce higher accuracy and speed that can use learning style identification.

Spatiotemporal learning: The issue of learning style identification also concerns an important dimension of student learning, referred as the spatiotemporal learning preference. The spatiotemporal study can be extended from space-time presentation of learning capability and learning preference change attributes to regional educational strategy development guided by machine learning models.

Grade prediction: The relationship between learning style and classroom examination score can be considered as one of the chief project research content in terms of applying machine learning algorithms to learning style identification to some extent. These studies mainly include training various algorithms to achieve score prediction according to individual learning style behavior.

Although many efforts have been made in the fields mentioned above, there are still a large number of open challenges waiting for researchers to explore: The larger issue is how to get higher quality, objective, and effective learning style data, which can be used to improve the training, optimization and learning of various kinds of machine learning models. From a methodological perspective, how to improve the adoption of current advanced machine learning algorithm models in education systems, a kind of difficult cross-platform model intelligently interacting process, this needs further research, especially for the intelligence mechanisms required at a mass scale.

Beyond the mainstream methods proposed above, following are some justification why researchers may continue to dig into related fields in the future: In conclusion, future research needs to provide users with more user-friendly machine learning tools that can help educators and other related staff with relatively less machine learning knowledge use machine learning tools for their own research. In terms of the methodology itself, the results of the existing algorithm and model often show various problems when processing large and complex educational data. In the meantime, there is no research on the long-term effect of advanced machine learning models to facilitate education or the investigation of the user usage behavior of these advanced learning-related algorithms. Particularly, using predictive learning tools on students' academic performance, many privacy and ethical issues be paid attention to.

4. Related Literature Review

The following is a summary of the 19 relevant papers in this review, including the authors, titles, publication years, and main findings.

Title	Author	Publication Year	Findings
"Adaptive Gamification in Science Education: An Analysis of the Impact of implementation and Adapted game Elements on Students' Motivation"[1]	Zourmpakis, Alkinoos-Ioannis[1]	2023	Through investigations of science education, an overview is given of the adoption of adaptive gamification via machine learning in analyzing the student's behavior in the gamified system. This system is employed to identify learning styles and adjust educational content.
"The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory Validation and Associations with Personality, Corporate Distrust, and General Trust"[2]	Schepman, Astrid[2]	2023	Highlighting the potential of AI and machine learning to personalize the learning experience by identifying and catering to individual learning styles, sentiment analysis and clustering algorithms were used to measure acceptance and concerns about AI-powered educational tools.
"Automatic text generation using deep learning: providing large-scale support for online learning communities"[3]	Du, Hanxiang[3]	2023	Deep learning is applications for generating texts automatically in educational environments. Analyzing students' written answers and feedback can help us find more styles and preferences which they can tend to learn better.
"Adapting gamified learning systems using educational data mining techniques"[4]	Daghestani, Lamya F.[4]	2020	The use of educational data mining to adapt a gamified learning system to meet the individual needs of students is explored, employing a variety of machine learning algorithms to analyze student performance and

			interaction data to identify different learning styles.
“Home appliances recommendation system based on weather information using combined modified k-means and elbow algorithms”[5]	Jaafar, Basim Amer[5]	2020	Collaborative filtering and clustering algorithms are discussed that can identify learning styles based on student preferences and interactions.
“A difficulty ranking approach to personalization in E-learning”[6]	Segal, Avi[6]	2019	Explore the EduRank algorithm that combines collaborative filtering algorithms and voting methods that can provide personalized content for students.
“Advancing NATO's quality assurance education by implementing the 'learn-watch-ask' training model”[7]	Bălănescu, Radu Emilian[7]	2023	This paper discusses the implementation of IBM WatsonX assistant as a conversational AI chatbot into LWA, and shows how it performs better than generative pre-training transformer (GPT) AI models at providing authentic, reliable, and simple-to-use feedback.
“Future Trends for Human-AI Collaboration: A Comprehensive Taxonomy of AI/AGI Using Multiple Intelligences and Learning Styles”[8]	Cichocki, Andrzej[8]	2021	Some trends and concepts for developing a new generation of future Artificial General Intelligence (AGI) systems are discussed, suggesting that future AI systems will not only be able to communicate with human users and with each other, but will also be able to effectively exchange knowledge and wisdom, have the ability to cooperate, collaborate and even co-create new and valuable things, and have the ability to metalearn.
“Digital Education and Artistic-Visual Learning in Flexible University	González-Zamar, Mariana-Daniela[9]	2020	Bibliometric techniques were used to study the identification of global trends in digital education and their links with learning in arts and visual education in higher

Environments: Research Analysis”[9]			education.
“Predicting exclusive breastfeeding in maternity wards using machine learning techniques”[10]	Oliver-Roig, Antonio[10]	2022	The aim of this study was to predict exclusive breastfeeding during postpartum hospitalization by means of ML algorithms and to explain the behavior of ML models to support decision-making.
“An optimized deep nonlinear integrated framework for wind speed forecasting and uncertainty analysis”[11]	Wang, Jujie[11]	2023	In this paper, a segmented multimodal deep learning integrated model based on periodicity is proposed to further improve the reliability of wind speed prediction.
“Revisiting Pontoppidan: Sentiment analysis and topic modelling on `Eagle's Flight'”[12]	Vlachos, Evgenios[12]	2023	An attempt was made to validate the existing view of The Flight of the Eagle based on a classical literary analysis (qualitative part) from a different perspective, digital text analysis (quantitative part). Digital analysis focuses on sentiment analysis and thematic modeling as a way to discover differences in different versions of the same story.
“A Cross-Sectional Machine Learning Approach for Hedge Fund Return Prediction and Selection”[13]	Wu, Wenbo[13]	2021	Equipping the prediction model with a set of idiosyncratic features applies four machine learning methods to cross-sectional return prediction for hedge fund selection. These features are derived from historical returns of hedge funds and capture information specific to various funds.
“GenoMus: Representing Procedural Musical Structures with an Encoded	Lopez-Montes, Jose[14]	2022	Featuring applications to augment music programming with musical creativity, computational musicology, and machine learning algorithms. This highly

Functional Grammar Optimized for Metaprogramming and Machine Learning”[14]			homogeneous and modular approach simplifies metaprogramming and maximizes the search space. It abstracts and compactly represents musical knowledge as arrays of pure numbers, optimizing the application of different machine learning paradigms.
“Do Male and Female Legislators Have Different Twitter Communication Styles?”[15]	Butler, Daniel M. M.[15]	2023	Personalization of political ads requires data collection from Twitter users, so we use the full corpus of tweets to categorize tweeter behavior. To use a supervised learning approach, we first hand-code a subset of sample tweets, and then train our ML algorithm until most of the tweets are categorized.
“Supervised Machine Learning-Assisted Driving Stress Monitoring MIMO Radar System”[16]	Lopez, Maria-Jose[16]	2023	A new method using multiple-input multiple-output (MIMO) radar systems is proposed to accurately assess driver stress levels by measuring physiological signals and driving behavior. The acquired data is utilized to train a fully connected neural network (FCNN) model and evaluate the performance of volunteers in different driving environments.
“Environment Classification Using Machine Learning Methods for Eco-Driving Strategies in Intelligent Vehicles”[17]	del C Julio-Rodriguez, Jose[17]	2022	Dynamic variables from Inertial Measurement Unit (IMU) sensors and instantaneous energy consumption measurements are utilized. The feasibility of a method to classify the vehicle driving environment is explored. This can be used to provide accurate information for path planning, energy optimization or safety purposes.
“An improved faster-RCNN model for	Albahli, Saleh[18]	2021	A customized Faster-Regional Convolutional Neural Network (Faster-RCNN) is introduced, thus

handwritten character recognition”[18]			proposing an effective and efficient HDR system that analyzes the performance of the proposed method on a standard MNIST database that is diverse in terms of lighting conditions, chromaticity, variations in digit shapes and sizes, as well as the onset of blurring and noise effects.
“Bispace Domain Adaptation Network for Remotely Sensed Semantic Segmentation”[19]	Liu, Wei[19]	2022	Supervised learning for semantic segmentation in remote sensing usually has high requirements for pixel-level ground truth from test images (target domain). Data labeling for semantic segmentation is both laborious and time-consuming. In order to reduce the effort of manual annotation, domain adaptation (DA) utilizes the annotated images already available from other sources (source domain) to classify the images in the target domain. In this paper, we propose a dual spatial alignment network for DA that is capable of extracting features in both image and wavelet domains.

5. Conclusion

We believe that, despite limitations, the overall trend in the literature points to a bright future in the use of advanced ML techniques to address learning styles. We find that current research generally supports the view that ML can be used to improve learning by personalization, user engagement, and other relevant educational outcomes. But as with other new research areas, several challenges have yet to be properly addressed: the development of better learning algorithms, the requirement for larger and more diverse datasets, and the important ethical implications of personalized learning.

Another important consideration involves more strategic diversity in the educational setting, which is also relevant in ML experiments. In any case, future research should focus on enhancing, in many ways, the state of the art in ML, setting new directions in empirical research, and broadly generalizing these settings in various domains of the education system. The integration between learning styles and more sophisticated ML algorithms has the potential to revolutionize educational practices. Overall, we can infer that, in more general terms, the reviewed literature calls for instructional personalization, hybridization, spatiotemporal considerations, and support for system performance assessment.

Today, research should primarily be concerned with how to improve the efficiency of algorithms, what kind of datasets we need to use, and how to generalize it in different learning environments and educational systems. Enhanced algorithms represent a new era of learning style identification in education. The improvement and conduction of advanced methods in this area will help us reach even further milestones There are several challenges to overcome. Basic research is still required to improve algorithmic performance and conduct empirical research to expand its scope.

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