Towards Personalized Learning Environments: Using Machine Learning to Predict Students' Learning Preferences in a Mixed Reality Environment.

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***Abstract*— This research-to-practice full paper describes the machine learning techniques for predicting students' learning preferences and cognitive load in a mixed reality environment. As the construction industry increasingly adopts sensing technologies, the demand for hands-on learning experiences in construction education becomes imperative. However, challenges arise in educating the future workforce due to limited access to construction sites for practical learning and the high costs associated with these technologies. To overcome these obstacles, educators are turning to virtual learning environments, such as mixed reality (MR), to provide engaging learning experiences. While MR has been utilized in construction education for simulating activities, the design of such learning environments often neglects to account for the varying learning preferences necessary for effective navigation and optimal learning outcomes. This makes it necessary to develop intelligent learning environments that can detect students' learning preferences and present information based on individual preferences. Extant studies have shown that eye movement data, particularly fixations from virtual learning environments, provide valuable insights into users' cognitive processes. Studies have also shown that leveraging machine learning algorithms enables the analysis and interpretation of eye-tracking data, offering deeper insights into students' learning preferences. In this study, nineteen undergraduate students participated in hands-on activities involving the implementation of sensing technologies within an MR learning environment. Questionnaires on learning preferences were used to assess individual learning preferences. By employing machine learning techniques on eye-tracking data and subjective evaluations of learning preferences, the study presents models that can detect students' learning preferences. The study compared performance metrics from three classifiers - Ensemble, Neural Network, and K-Nearest Neighbors (KNN) and the Ensemble classifier was identified as the most accurate, achieving an accuracy of 83.3% for the test model. The findings highlight the potential of machine learning models in detecting learning preferences most effectively for the user's interactions. The classification models, when implemented in the MR environment, can identify users who may require additional support tailored to their specific learning preferences. Thereby enhancing their interaction with the MR learning environment. Understanding and accommodating diverse learning preferences in MR learning environments can offer personalized experiences for effective engagement and knowledge retention in construction education. By tailoring instructional methods to individual preferences, educators can create inclusive environments that foster deeper comprehension and maximize learning outcomes.**

Keywords*— Machine Learning, construction education, Learning preferences, Intelligent learning environments, Mixed reality environment.

I. Introduction

There is a growing adoption of sensing technologies in the construction industry. As reported by Ogunseiju, Akanmu and Bairaktarova [1], construction companies currently adopt various sensing technologies such as laser scanners, drones, ground penetrating radars, global positioning systems (GPS), and real-time location sensors (RTLS). This has resulted in several benefits, such as optimized productivity and efficiency, improved safety, and significant improvement in the extraction and sharing of project data. It is projected that as this productivity continues to increase, the construction industry can ramp up an additional 2% increase in the global economy [2]. As the construction industry increasingly adopts sensing technologies [3], there becomes a need to prepare the future workforce to implement sensing technologies in the construction industry. In addition to the need to train the future workforce in this area, research such as Zhang, Arditi and Liu [4] has revealed that integrating sensing technologies such as laser scanning in construction education curricula can improve at least seven student learning outcomes (SLOs), as required by the American Council of Construction Education (ACCE). However, challenges arise in educating the future workforce due to limited access to construction sites for practical learning and the high costs associated with these technologies.

To address these challenges and equip students with the requisite technical skills, several studies have investigated the efficacy of virtual environments such as mixed reality and virtual reality. For example, Cheng, Gheisari and Jeelani [5] employed virtual reality to train construction workers on the safety challenges of drones. Similarly, Ogunseiju, Akanmu [6] implemented a mixed-reality learning environment for learning sensing technologies in construction education. The students noted the learning environment as fun, exciting, and informative. In such learning environments, students often encounter cognitive overload because information is often presented in visual and audio mode, and such information is required to be processed by human working memory. The theory of cognitive load explains that human working memory is limited, and instructions should be designed appropriately to promote the effective processing of the learning contents [7]. Likewise, students' learning preferences can also greatly impact their cognitive load and learning outcomes in a virtual environment [8]. Learning preference similar to learning style is defined by Zhang, Du [9] as "the way to obtain and process information". Huang, Luo [8] explained that students with certain learning preferences must incur a higher cognitive load to achieve the same learning outcomes as other students. This is because students learn in different ways. As stated by Yfanti and Doukakis [10], "individual learners show preferences for the mode in which they receive information (e.g., visual, auditory, kinesthetic)." Some may prefer more visual information for effective learning experiences, and other students may do better when learning content contains more words or graphics.

While the idea of tailoring instruction to specific learning preferences has been debated, with some arguing that it does not significantly enhance learning outcomes [10-15], the focus has increasingly shifted toward personalizing learning experiences to better align with individual preferences and needs [9, 16-18]. Studies have shown that understanding and adapting to these preferences can positively impact student learning outcomes [9, 16, 18]. For example, Hsieh and Chen [19] utilized handheld devices to implement personalized learning strategies that address the diverse cognitive styles of students. Likewise, Tlili, Denden [20] developed an educational game that adapts its content based on the individual personalities of learners and found out that personalized educational games decreased cognitive load. However, researchers and designers of virtual learning environments have failed to consider how personalized experiences, based on individual learning preferences, can enhance learning outcomes. As a first step to investigating personalized learning environments for construction education, this study develops models that can detect students' learning preferences during the implementation of sensing technologies in a mixed reality environment. This study employs machine learning algorithms on eye-tracking data to detect students' learning preferences. The findings highlight the potential of machine learning models in predicting students' learning preferences. By tailoring instructional methods to individual preferences, educators can create inclusive environments that foster deeper comprehension and maximize learning outcomes. Moreover, the integration of machine learning algorithms enables real-time assessment and adaptation of learning environments, paving the way for more intelligent educational technologies in the future.

II. BACKGROUND

In this section, reviews of sensing technologies in the construction industry, personalized learning environments in construction education, and the theoretical framework of the study are presented.

A. *Sensing technologies in the construction industry*

As explained by Arabshahi, Wang [21], sensing technologies can be location-based technologies (such as RTLS, Radio Frequency Identification (RFID), ultra-wideband (UWB) technology, and GPS) and vision-based technologies, such as photographs and video recording technologies. The authors further categorized sensing technologies into wireless sensor network technologies (WSN), (e.g., temperature sensors, light sensors, and pressure sensors), often used for wireless communications of data between resources and recording devices. These sensors are often efficient in locating and tracking construction materials for improved safety, enhancing situational awareness, and hazard exposure analysis [21]. Physiological sensing technologies, such as Electroencephalograms (EEGs), are used to improve workers' safety by detecting stress, fatigue, and attention levels. While some categories of sensing technologies (e.g., physiological sensors) are still being explored in the construction industry, others, such as vision-based and location-based sensing technologies, have achieved a wide level of adoption. Ogunseiju, Akanmu and Bairaktarova [1] revealed how companies such as DPR Construction, Skanska, and Hensel Phelps are utilizing several vision-based technologies and achieving benefits like improved site logistics, better quality control, and cost savings. To develop the future workforce, it becomes important that students acquire the necessary technical skills needed to thrive in this technically advancing era of construction.

B. *Personalized learning environment in construction education*

Personalized learning is a unique approach to teaching and learning that provides opportunities for students to engage in a diverse set of learning experiences, identify and own their learning preferences, explore relevant and authentic topics, and strengthen critical thinking, creativity, and collaboration skills [22]. Personalized learning focuses on optimizing the learning pace, instructional preferences, and learning content to suit each learner's needs [23]. Personalized learning has been explored in education, and specifically, extant studies have investigated ways to leverage personalized learning for the design and development of learning environments. For example, Adas, Shetty and Hargrove [24] investigated virtual reality and augmented reality for personalized learning of engineering designs. In Adas, Shetty and Hargrove [24], virtual instructions were developed to integrate virtual models and visual cues for personalized learning. In construction, personalized learning environments have been investigated for improving the health and safety of construction workers [25]. Kang and Ryoo [26] explored personalized learning for teaching students building information modeling in construction education. Kang and Ryoo [26] employed personalized learning focused on creating flexible, anytime learning and student-driven learning paths by encouraging students to leverage online materials such as YouTube and Facebook videos for a detailed understanding of the class project. There is no information on the assessment of personalized learning environments for construction education, specifically for training the future workforce, which inspires the need for this study.

C. *Theoretical framework*

Cognition plays a pivotal role in determining an individual's learning preference [27], as it encompasses the mental processes involved in acquiring knowledge and understanding through thought, experience, and the senses. Individuals' cognitive preferences, such as how they perceive, process, and remember information, influence their learning preferences [28]. For example, some learners may have a preference for visual information, while others may prefer auditory or kinesthetic modalities. These cognitive factors interact with learning environments and instructional materials, influencing individuals' learning experiences [27]. Moreover, cognitive theories provide frameworks for assessing and addressing individual differences in learning preferences, guiding the design of personalized learning experiences. This study is guided by the principles of Cognitive Load Theory (CLT). Researchers [7] have adopted CTL to design learning environments where information is presented in a manner that stimulates learning and promotes intellectual performance. The theory posits that the working memory is limited while the long-term memory is unlimited. However, CTL further explains that the limitations of working memory can be mitigated by developing several elements of information as one element in cognitive schemata by automating rules and presenting information with different modalities [7]. To understand the effects of learning contents of cognitive load in the mixed reality environment, the study further explores the Cognitive Theory of Multimedia Learning (CTML) [25]. CTML explains that learners, being active participants, develop insightful connections between words and pictures and learn more deeply than they would have with just words or pictures alone [29]. CTML further explains that human memory can be classified as working memory, long-term memory, and sensory systems. CTML proposes that the processing of visual and verbal information from visuals and audio occurs in the sensory system, while long-term memory retains cognitive constructs and manages information [30, 31]. To understand the impacts of learning materials and learning environments on students' learning preferences, this study adopts the principles of CTML. The study seeks to understand how students' learning style preferences impact their processing of visuals and audio information during cognitive activities in an MR learning environment. Since eye-tracking data possess information about cognition, the study seeks to develop models that can predict learning preferences based on eye-tracking data.

D. *Research question*

According to Sorden [29], CTML is established on three important tenets: the tenets of dual channel, the limited capacity assumption, and the active processing assumption. The dual-channel tenets believe that working memory has visual and auditory channels. In contrast, the limited capacity tenets are based on the theory of cognitive load and explain that each subsystem of the working memory is limited. Hence, it is important that while learning in a mixed reality environment, learners' limited working capacity is effectively utilized to minimize cognitive overload. To do this, learning environments must be designed to adapt to each learner's cognitive load. Lastly, the tenets of active processing suggest that meaning is constructed meaningfully when learners devote attention to the learning material. However, according to Antelm-Lanzat, Gil [32], [33], learning preferences often impact the way learning materials are understood and coherently structured. Hence, to promote effective learning experiences, learning content must be designed and adapted to students' learning preferences. This leads to our **research question:** What is the effectiveness of machine learning models for predicting students' learning preferences in a mixed reality environment?

III. METHODS AND ANALYSIS

This section details the methodology adopted in this study. This section explains the experimental procedure, data collection, and data analysis process (Fig. 1).

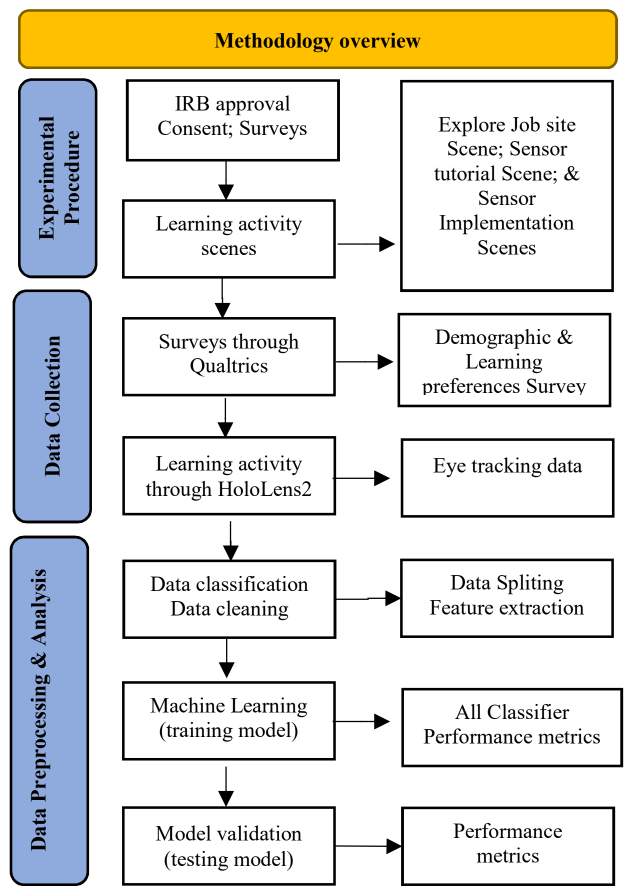

Fig. 1: Overview of methodology

A. *Experiment Procedure*

a. *Participants*

The learning environment was implemented in a Construction Technology course (BC 2620) at Georgia Tech as a part of the course curriculum. The participants were 19 students with an average age of 18-24 years. The participant group was diverse in both gender, race, and ethnicity, reflecting a broad spectrum of backgrounds. Students were recruited through the institution's Canvas platform, where participation in the mixed reality interaction was a graded component of their course curriculum. Additionally, the majority of students had significant prior experience interacting with virtual learning environments, including Mixed Reality, Virtual Reality, and Augmented Reality.

b. AR Head-Mounted Display

The AR Head-Mounted Display (HMD) adopted for this study was the HoloLens 2, which is an advanced augmented reality head-mounted display (AR HMD) developed by Microsoft. The AR HMD provided eye and head gaze data, which is pivotal for understanding user engagement, and cognition.

c. The Learning Environment and Activities

This study was guided and approved by the Institutional Review Board (IRB) at Georgia Tech. Before the beginning of the study, students were required to provide their consent, after which they were immersed in the learning environment through the AR-HMD. The mixed reality (MR) learning environment for learning sensing technologies, as shown in Fig. 2, was developed using the Unity3D game engine and consists of three distinct learning scenes: The explore jobsite scene, the sensor tutorial scene, and the sensor implementation scene. 'Scene' represents environments where learning occurs, as described in detail by the preceding study [34]. For this study, participants were required to interact with the three learning scenes. All scenes were equipped with a virtual assistant and menu interfaces (Fig.2) that explained the learning activities in each scene. In the Explore Jobsite Scene (Fig 2a), participants were asked to observe at least three (3) construction activities, the types of resources involved in each activity, and interactions between each of the resources, and identify the risks involved and the required sensing system to mitigate the risks. The Sensor Tutorial Scene (Fig 2b) offers a step-by-step guide on implementing five sensing technologies (Laser scanner, Radio Frequency Identification Device (RFID), IMU, GPS, and drones) within the environment. While in the sensor implementation (Fig.2c), users were asked to implement the selected sensor on the selected activity to mitigate the identified risk.

B. Data Collection

a. Questionnaires

The study employs a learning style questionnaire from the University of California, Merced (learning.ucmerced.edu). The questionnaire categorizes preferences into Visual, Auditory, and Tactile (Kinesthetic) learners. The visual category is further divided into Visual and Read/Write learners based on the learning preferences model introduced by Neil Fleming [35]. According to Neil Fleming [35], there are four major types of learning preferences (VARK: Visual, Auditory, Read/write, and Kinesthetic). Visual Learners learn things using real-time visual tools such as graphs, charts, diagrams, and symbols. Auditory Learners prefer to understand through listening such as lectures, discussions, and tapes. The Tactile/Kinesthetic learners engage best with real-time experiences such as hands-on projects. Read/write learners prefer information displayed in written form, such as lists and text [35]. It is important to emphasize that the questionnaire used for this study is based on the VARK model because it aims to capture how students interact with learning materials in a way that aligns with their individual learning preferences.

b. Eye-tracking data

Eye-tracking data is valuable in assessing student learning preferences as it offers a direct, quantitative measure of where and how students allocate their visual attention during learning tasks [36]. A study by Luo [37] utilized eye-tracking data to identify student learning preferences and compared the result with the learning style classification obtained from the subjective questionnaire. It was noted that eye-tracking data accurately predict student learning preferences. Eye-tracking data can reveal patterns [37] indicative of different learning preferences [38]. For example, individuals with a preference for visual learning may exhibit longer fixations on graphical elements or images, while those who favor verbal learning may spend more time reading text. Moreover, eye-tracking data is collected non-intrusively, preserving the natural learning environment and ensuring that the data reflects genuine interaction with the material [38]. To predict students' learning preferences during the interactions with the learning environment, this study adopted eye-tracking data afforded by the Hololens 2, which provided information such as head gaze, duration, head origins, and positions.

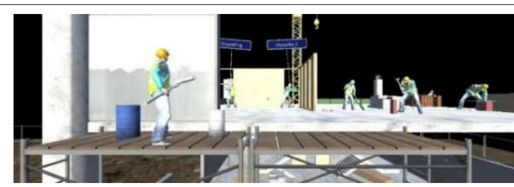

Fig. 2a. Explore Jobsite Scene

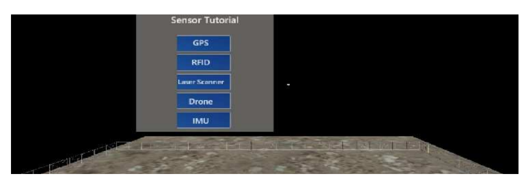

Fig. 2b.Sensor Tutorial Scene

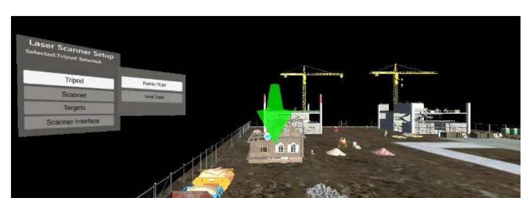

Fig. 2c. Sensor Implementation Scene

Fig. 2. Mixed Reality Learning Environment

C. Data Preprocessing

a. Questionnaires on Learning preferences

The learning preferences survey has 24 questions in total, and the options were further analyzed based on the grading system provided by the institution. The options for each question are often (5 points), sometimes (3 points), and seldom (1 point). The learning style questions were categorized into Visual, Read/write, Auditory, and Tactile (Kinesthetic) learners. The survey was analyzed using descriptive statistics in Microsoft Excel, and Participants were categorized according to their respective learning preferences. Interestingly, during the analysis, the research team identified a few participants who exhibited a combination of two or more learning preferences. This finding aligns with studies by Jurenka, Stareček [39], and Kuttattu, Gokul [40], which also suggests that students can possess multiple learning preferences. This means that learning preferences are not fixed and that students can benefit from multiple learning modalities. Therefore, the input data (eye tracking data) were analyzed based on different learning preferences (Table 1).

TABLE I LEARNING PREFERENCES CLASSIFICATION.

Classes	Students per learning preference	
	No of students	***Percentages***
Visual	5	26.3%
Auditory	3	15.8%
Kinesthetic	3	15.8%
Read/Write	3	15.8%
Visual+ Kinesthetic	2	10.5%
Visual+ Auditory	1	5.3%
Visual + Auditory + Kinesthetic	2	10.5%
Total	19	100 %

b. Eye-tracking data

Eye-tracking data were used to understand users' cognition during interactions within virtual environments. In this study, fixations were extracted to analyze where participants focused their attention while using the HoloLens 2 augmented reality (AR) device. Fixations represent instances where the eyes remain relatively still and focused on a specific point in the visual field. To extract fixations, we recorded fixation duration, measured in milliseconds (ms), which denotes the length of time a participant's gaze remained fixed on a particular area. According to Sekhri et al [41], fixation duration may range from 150 to 650 ms [41]. Similar studies by Ogunseiju et al [34]; Olsen [42]; and [43] said a minimum fixation duration between 50 -150 ms can be adopted for tasks such as reading and visual search [44]. For this study, a minimum fixation of 75 ms and a maximum fixation duration of 650 ms were utilized. Fixation start and end times were also extracted to precisely identify the duration of each fixation event. This can provide an understanding of student reading and cognitive performance [45]. In addition, the head origin coordinates (X, Y, Z) were utilized to provide additional insights into the spatial distribution of fixations and how participants orient themselves within the AR environment [46, 47]. As outlined in Table 2, data inputs utilized for developing the machine learning models include fixation duration, fixation start time, fixation end time, and head origin coordinates. These data inputs are crucial for understanding where, when, and for how long participants focus on different elements of a visual scene, which can reveal insights into their users' cognition, such as visual attention and interaction patterns within the AR learning environment [44].

Table II DATA INPUTS AND THEIR DESCRIPTION

Data Inputs	Description	
	Description	***References***
Fixation duration	Fixation time measured in milliseconds (ms)	[41]
Fixation Start time	The time when the fixation begins	[45]
Fixation end time	The time when the fixation ends	[45]
Head origin X	X-coordinate of the head's position at fixation	[47]
Head origin Y	Y-coordinate of the head's position at fixation	[47]
Head origin Z	Z-coordinate of the head's position at fixation	[47]

D. Machine Learning Data Classifications

The classification model was trained on data from 19 participants after categorizing them into various learning preferences (Table 2) and extracting the fixations. The dataset was divided into training and testing sets, with 90% of the data allocated for training and 10% for testing, as recommended by Uçar, Nour [48]. This split allowed model training on a significant portion of the data while reserving a separate set to evaluate their performance.

Statistical features such as mean, median, and mode were employed as input features for the models, contributing to a total of eighteen (18) features considered in the analysis. The training of the models was conducted using MATLAB. Cross-validation, a technique that helps prevent overfitting by dividing the training dataset into smaller subsets, was adopted. Each subset is used as a temporary testing set, while the remaining data serves as the training set. This process was repeated multiple times, ensuring that each data point was used for both training and testing. Cross-validation enhances the robustness of the model by providing a more accurate estimate of its performance on unseen data. The study then adopted a wide array of machine learning classifiers, including Ensemble methods, Neural Networks (NN), Support Vector Machine (SVM), Ensemble, Naıve Bayes, decision tree, Logistic Regression (LR), and kernel and K-Nearest Neighbors (KNN), to explore different algorithmic approaches to the data. The decision to use all available classifiers was driven by the desire to compare their effectiveness and identify the best-performing model for our specific dataset. The top-performing classifiers identified through cross-validation were ensemble, NN, and KNN.

The trained models were then evaluated using performance measures such as accuracy, precision, recall, and F1-score to assess their effectiveness in classifying the data [49]. Accuracy measures the proportion of correct predictions among the total number of cases evaluated [49]. Precision assesses the classifier's ability to identify only relevant instances, while recall evaluates the ability to find all relevant instances within the dataset [50]. The Receiver Operating Characteristic curve (ROC) is a graphical representation that assesses the performance of the model [51]. The F1 score provides a balance between precision and recall, offering a single metric for performance comparison. These measures were calculated for each model and used to compare their performance on both the training and test datasets, providing valuable insights into their effectiveness and generalization capabilities. A multi-class confusion matrix was generated to assess the classification model. The matrix contained rows and columns with the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) [49]. Finally, the classifiers were tested on the reserved test data (unseen dataset) and were used to validate (test the performance) the classification models. The results are presented in the next section.

IV. Results

This section focuses on the results of the study, wherein the confusion matrix for the top classifier is explained, and the performance of the top three classifiers (Table 3) is compared using the afore-discussed performance measures.

A. *Performance Metrics of the Trained Model*

The performance metrics of three classifiers—Ensemble, Neural Network, and KNN—were evaluated, with the Ensemble classifier achieving the highest accuracy of 82.2% for the trained model. The Ensemble classifier demonstrated high precision and recall rates across various learning preferences, indicating a reliable prediction capability. The F1 Score, which balances precision and recall, was also notably high, suggesting that the classifier is robust in its predictions. Precision, recall, accuracy, and F1 scores were assessed for each learning preference category. The Ensemble classifier achieved precision values ranging from 75.8% to 88.4%, recall values from 64.9% to 91.8%, and F1 scores from 60.7% to 88.2% across different learning preferences. Similarly, the Neural Network classifier attained precision values ranging from 69.7% to 92%, recall values from 67.1% to 88.8%, and F1 scores from 68.4% to 90.9%. In comparison, the KNN classifier demonstrated precision values ranging from 61.4% to 87.4%, recall values from 54.8% to 86.7%, and F1 scores from 57.9% to 85.9%.

B. *Model Validation with Test Data*

To validate the trained model, the model was tested with the test dataset separated during the cross-validation phase. It was tested with all classifiers, and interestingly, Ensemble emerged as the best classifier with an accuracy of 83.3%. The output, termed the test model, encapsulates the predicted classifications for the test data [52]. The efficacy of the test models was gauged through performance metrics delineated in Table 4. The confusion matrix, depicted in Figure 3, was derived from the model's predictions on the test dataset. The test performance metrics indicate a significant improvement from the training to testing phases. Table 4 displays the performance metrics of the Ensemble classifier. The precision rates for the Read/Write and Visual + Kinesthetic styles are noteworthy at 94.4% and 96.0%, respectively. These precision rates signify the proportion of correctly identified instances among all instances classified as a particular learning preference. Therefore, when the model predicts a student's preference for these learning preferences, there is a high likelihood of correctness.

On the other hand, recall rates, representing the proportion of actual instances of a class that were correctly classified by the model, were highest for the Auditory and V+ Kinesthetic learning preferences, reaching 94.00% and 92.30%, respectively. This indicates the model's proficiency in identifying students inclined toward these learning preferences. However, the model exhibits lower performance in both precision and recall for Visual + Auditory and Visual + Auditory + Kinesthetic (V+A+K) learning preferences, with rates of 75.00% and 70.40%, respectively. These findings suggest potential challenges in accurately identifying students with these composite learning preferences, leading to a higher likelihood of both false positives and false negatives. This indicates a need for model refinement to better capture mixed learning preferences.

V. Discussion

Based on the results from the test model, it can be concluded that the Ensemble classifier shows promising results in predicting students' learning preferences within a mixed reality environment with an accuracy of 83.3%, which can be instrumental in personalizing educational experiences and improving learning outcomes. This accuracy, while slightly lower, is comparable to the findings by Ikawati, Al Rasyid and Winarno [53] who obtained an accuracy of 90% with the Bagging algorithm of the Ensemble classifier. Their study also demonstrated that ensemble methods, such as gradient-boosted trees and Bagging, consistently outperformed single algorithms like Decision Trees, achieving accuracy rates of 89.80% and 84.30%, respectively. An ensemble classifier works well for detecting learning preferences due to its ability to combine multiple classifiers to produce better predictions [54]. In other words, an ensemble model combines several individual models to produce more accurate predictions and capture complex patterns and relationships in the data that might be missed by a single classifier [55]. This classifier has been identified by Rao [35] to effectively predict learning preferences. The high precision and recall in certain learning preferences further support the model's effectiveness, particularly in identifying Auditory, Read/Write, and Visual + Kinesthetic preferences. This can be attributed to some of the features of the learning environment. This includes a virtual assistant for providing audio guidance in the learning environment, visual representations of the construction site and sensing technologies, and a detailed menu interface for providing textual guidance on the learning activities in the environment. However, ensemble classifiers face challenges with predicting mixed learners such as V+A+K, and V+ Auditory. This may be due to insufficient representation of mixed learners' data in the training process, resulting in inadequate generalization of mixed learning preferences. To address this limitation, future research efforts could focus on enhancing the training dataset by collecting more mixed learners data. Additionally, incorporating additional features may improve the classifier's performance in predicting combined learners' patterns. By leveraging machine learning algorithms to analyze students' interactions within the virtual environment, educators can dynamically adjust the presentation of content, pacing of instruction, and level of cognitive challenge to maintain an optimal learning experience. For instance, auditory learners could be provided with more audio-based explanations, narrated presentations, and podcasts to facilitate information retention and comprehension. Kinesthetic learners could benefit from interactive, movement-based tasks and virtual manipulatives to reinforce conceptual understanding and promote engagement. Providing detailed textual instructions, reading materials, and written summaries can support these read/write learners. In a mixed reality environment, educators could incorporate extensive written guides or documentation that learners can access as they engage with the virtual tasks. By tailoring instructional interventions to match students' preferred learning preferences, educators can foster a more inclusive and effective learning environment that accommodates diverse learning needs and preferences.

TABLE III PERFORMANCE MEASURES OF TRAINED CLASSIFICATION MODELS

Classifiers	**Performance Measures**	**Learning preferences**						
		Auditory	***Kinesthetic***	***Read/Write***	***Visual***	***V+ Auditory***	***V+A+K***	***V+Kinesthetic***
Ensemble	Precision	84.9407	77.2959	87.23404	75.7575	56.98324	86.5921	88.3838
	Recall	91.7733	78.4974	85.1632	82.0463	64.96815	70.7762	84.1346
	Accuracy	82.1669	82.1669	82.1669	82.1669	82.1669	82.1669	82.1669
	F1 Score	88.2249	77.8920	86.18619	78.7766	60.71429	77.8894	86.2069
	Specificity	95.1232	95.5186	97.4095	92.6645	99.0970	98.8852	98.9371
Neural Network	Precision	87.60%	92.00%	75.60%	75.20%	76.60%	69.70%	82.40%
	Recall	88.80%	89.90%	77.20%	78.40%	68.80%	67.10%	80.80%
	Accuracy	81.00%	81.00%	81.00%	81.00%	81.00%	81.00%	81.00%
	F1 Score	88.1959	90.9378	76.39162	76.7666	72.49078	68.3752	81.5921
KNN	Precision	85.10%	63.60%	73.30%	65.50%	61.40%	78.40%	87.40%
	Recall	86.70%	66.10%	71.80%	73.70%	54.80%	61.20%	79.80%
	Accuracy	73.30%	73.30%	73.30%	73.30%	73.30%	73.30%	73.30%
	F1 Score	85.8925	64.8259	72.54225	69.3584	57.91256	68.7404	83.4272

Note: V = Visuals, A = Auditory, and K = Kinesthetic

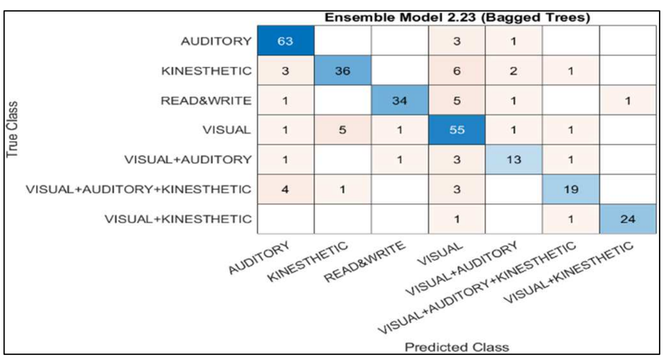

Fig. 3. No. of observation for the tested model

TABLE IV PERFORMANCE MEASURES OF THE TEST CLASSIFICATION MODEL

Classifier	**Metrics**	**Learning preferences**						
		Auditory	***Kinesthetic***	***Read/Write***	***Visual***	***V+ Auditory***	***V+A+K***	***V + Kinesthetic***
Ensemble	Precision	86.30%	85.70%	94.40%	72.40%	72.20%	82.60%	96.00%
	Recall	94.00%	75.00%	81.00%	85.90%	68.4.%	70.40%	92.30%
	Accuracy	83.30%	83.30%	83.30%	83.30%	83.30%	83.30%	83.30%
	F1 score	89.99%	79.99%	87.19%	78.57%	70.25%	76.01%	94.11%

Note: V = Visuals, A = Auditory, and K = Kinesthetic

VI. Conclusion

In this study, we explored the feasibility of using machine learning algorithms to predict students' learning preferences in a mixed-reality learning environment. The study compared performance metrics from three classifiers - Ensemble, Neural Network, and K-Nearest Neighbors (KNN) obtained through supervised machined learning. The Ensemble classifier was identified as the most accurate, achieving an accuracy of 83.3% for the test model. The high precision, recall, and F1 score of the Ensemble classifier across various learning preferences makes it stand out as particularly effective for predicting students' learning preferences across various modalities such as Auditory, Read/Write, and Visual Kinesthetic. This study also reveals that learners can possess a combination of two or more learning preferences, suggesting that learning preferences are not fixed and that students can benefit from multiple learning modalities. Furthermore, since the mixed reality learning environment was equipped with a virtual assistant (for audio learners), menu interfaces (for read/write learners), and visual representations of the learning activities (for visual and kinesthetic learners), this study further shows the importance of a learning environment that suits diverse learning preferences.

VII. Study limitations and future work

While this study provides valuable insights into the potential of machine learning to predict students' learning preferences in a mixed-reality environment, several limitations should be considered. Firstly, the limited number of features used in the analysis may have constrained the predictive power of the machine learning models. While the inclusion of mean, median, and mode provided valuable information about students' learning preferences, additional features such as variance, standard deviation, and range could enhance the accuracy and robustness of the predictive models. Furthermore, some studies question the validity of learning styles, arguing that tailoring instruction based on these styles may not significantly enhance learning outcomes. This controversy may limit the applicability of the findings presented in this study, given that a learning style questionnaire was used to assess students' learning preferences. In future work, one promising direction is to deploy the predictive models developed in this study for real-world virtual learning environments. Additionally, deploying the models in real-world settings would provide opportunities to collect continuous feedback and refine the predictive algorithms over time, further improving their accuracy and reliability.

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