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AUTOMATED LEARNING STYLE CLASSIFICATION USING AUTOENCODERS AND FELDER-SILVERMAN MODEL FROM STUDENTS' DIGITAL FOOTPRINTS

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Abstract

This study investigated machine learning approaches that utilize students' digital footprints to classify learning styles and compared them with the established Felder-Silverman model. A dataset of 120 students with detailed digital footprints was collected from an online course-management system. The students completed the Felder-Silverman learning style questionnaire. In addition to employing principal component analysis (PCA) for feature extraction, an autoencoder neural network was proposed in this study for unsupervised learning of an informative latent feature representation from the raw footprint data. The encoder features from the autoencoder and the principal components from PCA were input to the K-means and hierarchical clustering algorithms to classify students into learning styles. The predicted clusters were compared with true Felder-Silverman labels by calculating accuracy, precision, and recall. The results showed that the K-means algorithm achieved a significantly higher accuracy of 89.7% with autoencoder features compared with 85.2% with PCA features. The autoencoder model outperformed both PCA and traditional classifiers, such as decision trees. These results demonstrate the potential of using autoencoders to enhance feature learning from digital footprints for more precise learning-style classification.

Keywords

Machine Learning, Felder-Silverman Model, Digital Footprint, Principal component Analysis (PCA), k-means, autoencoder, deep learning, hierarchical clustering algorithm.

Introduction

The development of digital technology has revolutionized the way people learn and access educational resources. Learning management systems (LMS) have become one of the most popular platforms for delivering educational content, enabling learners to access learning materials and activities anytime and anywhere. Consequently, it has become increasingly important to understand how students learn and tailor educational content to their individual learning needs.

One approach to address this challenge is to classify students based on their learning styles. The Felder-Silverman model is a widely used classification system that categorizes students into four dimensions of learning style: active-reflective, sensory-intuitive, visual-verbal, and sequential-global. This model has been used to develop teaching strategies that

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align with students' learning styles and result in improved learning outcomes.

In recent years, machine learning has proven to be a powerful tool for analyzing large amounts of data and detecting patterns and trends. The use of digital footprints when interacting with digital systems provides a valuable source of data for machine learning algorithms. By analyzing digital footprints, it is possible to gain insights into the behavior and preferences of students, which can be used to improve the design of educational content.

Recent studies have explored the use of machine learning techniques such as clustering and neural networks with digital footprint data to classify learning styles (Shahiri et al., 2015; Chen et al., 2018). However, the use of deep learning methods such as autoencoders remains relatively unexplored. Autoencoders can learn latent feature representations from unlabeled data in an unsupervised manner, which can improve the performance of downstream tasks.

In this study, we propose using autoencoders along with PCA to extract informative features from digital footprints for classifying learning styles. The performance of clustering algorithms using autoencoder features was compared to that of PCA and traditional methods. The findings of this study will enhance our comprehension of the efficacy of machine learning in categorizing students according to their learning styles. The outcomes may also offer valuable insights into designing more efficient LMS and electronic courses customized to the learning requirements of individual students. Ultimately, this study has the potential to enhance the quality of education and boost student learning outcomes.

The motivation for this research stems from the growing need for personalized learning approaches in increasingly diverse educational environments. By leveraging machine learning techniques to analyze students' digital footprints, we aim to develop a more accurate and efficient method for classifying learning styles. This approach has the potential to significantly impact educational practices by enabling educators to tailor their teaching methods and materials to individual student needs without relying solely on self-reported questionnaires. Our study not only contributes to the field of educational data mining but also paves the way for more adaptive and inclusive learning environments. The successful implementation of this method could lead to improved student engagement, better learning outcomes, and more effective resource allocation in educational institutions.

This study presents several novel contributions that significantly advance the field of educational data mining and learning style classification.

1- Innovative Feature Extraction: We introduce a novel approach by applying autoencoder neural networks to extract non-linear features from students' digital footprints. Unlike traditional methods such as PCA, which assume linear relationships, our approach captures complex, non-linear patterns in student behavior data, leading to more nuanced and accurate learning style classifications.

2- Integration with Felder-Silverman Model: Our study uniquely combines deep learning techniques with the established Felder-Silverman learning style model. This integration

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bridges the gap between traditional educational theory and cutting-edge machine learning, offering a more robust and theoretically grounded approach to learning style classification.
3- Real-time Adaptation Potential: By demonstrating improved classification accuracy, our method paves the way for real-time adaptation of learning environments. This advancement moves beyond static classifications, allowing for dynamic adjustments to instructional strategies as students' digital behaviors evolve throughout their learning journey.
4- Enhanced Personalization in LMS: Our approach provides a foundation for more sophisticated personalization in Learning Management Systems. By leveraging more accurate learning style classifications, LMS designers can create adaptive interfaces and content delivery mechanisms that respond to individual student needs with unprecedented precision.
5- Scalability and Generalizability: Unlike previous studies that often relied on small, context-specific datasets, our method is designed to be scalable and generalizable across different educational contexts. This contribution addresses a significant limitation in existing research and offers broader applicability in diverse learning environments.

The remainder of this paper is organized as follows: Section 2 provides a review of relevant literature on machine learning in education, learning style models, and digital footprints. Section 3 describes the research methodology, including data collection, feature extraction, and clustering algorithms used. Section 4 presents the results and discussion of the clustering performance using different approaches. Finally, Section 5 concludes the paper and suggests directions for future work.

Literature Review

Current Limitations in Learning Style Classification Methods

Traditional approaches to learning style classification have predominantly relied on self-reporting questionnaires and inventories. These methods, while widely adopted, face several significant limitations that have been increasingly scrutinized in recent educational research.

Fielder and Silverman Model

Fielder and Silverman's models are widely used classification systems for learning styles. This model categorizes students into four dimensions of learning styles: active-reflective, sensory-intuitive, visual-verbal, and sequential-global (Aljojo et al., 2015). This model has been used to develop teaching strategies that align with students' learning styles and lead to better learning outcomes (Šustickienė et al., 2020). Recent studies have highlighted the inherent limitations of such self-reporting methods of Fielder and Silverman's model in improving students’ learning outcomes. For instance, (Alharbi et al., 2017; Almarwani & Elshatarat, 2022) demonstrate one of the primary criticisms of self-reporting methods is their subjectivity and potential inaccuracy. Students' perceptions of

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their own learning preferences may not align with their actual behaviors or the most effective learning strategies.

Similarly, Rahim et al. (2021) utilized Fielder and Silverman's model to create a personalized learning approach for computer science students. The findings indicated that students who received personalized instruction tailored to their learning styles achieved better academic results compared to those who did not. These studies highlight the effectiveness of Fielder and Silverman's model in enhancing student learning outcomes. Teachers can enhance student engagement, motivation, and academic performance through its implementation.

(Nan Cenka et al., 2022; Nafea et al., 2019) focused on the use of technology to enhance students' learning experiences. Nan Cenka et al. proposed a personalized learning environment that utilizes an ontology-based conceptual model to enrich lifelong learning. Nafea et al. introduced a novel algorithm for recommending learning materials based on students' learning styles. These studies highlight the significance of acknowledging individual differences and customizing the learning experience to meet each student's requirements. Through technology, educators can establish personalized learning environments that foster student engagement, enhance learning outcomes, and improve the overall learning experience.

The potential of digital footprints for understanding learning behaviors

In recent years, the proliferation of digital learning environments has given rise to a new source of data for understanding student behavior: digital footprints. These footprints, defined as the traces of activity left behind by students in digital spaces, offer unprecedented insights into learning processes and behaviors. The potential of digital footprints to revolutionize our understanding of learning behaviors has garnered significant attention in educational research

Types of Digital Footprints in Learning Environments

Digital footprints in educational contexts encompass a wide range of data types. Clickstream data, which records every interaction a student has with a digital platform, provides a detailed map of navigation patterns and engagement with course materials (Pavlenko et al., 2021). Time spent on resources offers insights into student persistence and potential areas of difficulty. Interaction patterns, including forum posts, peer collaborations, and communication with instructors, shed light on social learning behaviors and engagement levels (Pozdeeva et al., 2021).

More sophisticated digital footprints include data on content creation (e.g., essays, projects), quiz and assignment performance, and even keystroke patterns that can indicate cognitive load and writing processes (Golder & Macy, 2014).Video interaction data, such as pausing, rewinding, or skipping through instructional videos, can reveal students' attention patterns and comprehension difficulties (Kim et al., 2014).

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The digital footprint (DF) refers to the traces of user activities left behind when interacting with digital systems (Pavlenko et al., 2021). In the educational context, the digital footprint can provide valuable data for the analysis of student behavior and preferences (Pozdeeva et al., 2021). This data can be used to improve the design of educational content, personalize instruction, and increase student learning outcomes Several studies have investigated the use of digital footprints in learning management systems (LMS). For example, (Sahni, 2023) objectively examined the potential of learning analytics in assessing student engagement and academic performance in an online learning environment. This study included 120 students who participated in an online course. Learning analytics was used to track student engagement with the course materials, such as how often they logged in, how much time they spent on the course, and how they participated in the discussion forums. Students' academic performance was assessed by their grades on the quizzes and exams. The results showed a positive correlation between student engagement and academic performance in the online learning environment. In addition, learning analytics provides valuable insights into students' learning behavior and could be used to predict academic performance. This study concludes that learning analytics have the potential to improve student engagement and academic performance in online learning environments.

(Buitrago-Ropero et al., 2020) conducted a systematic mapping study to examine the literature on digital footprints in education between 2005 and 2019. This study aimed to identify the main topics, research methods, and publication venues related to digital footprints in education. The study analyzed 91 articles and identified six main topics: (1) digital identity, (2) Digital citizenship, (3) privacy and security, (4) learning analytics and assessment, (5) digital literacy, and (6) teacher training. The authors found that most studies focused on digital identity and citizenship, and that qualitative research was the most used research method. The study also showed that there is no consensus on the definition and concept of digital footprint. The results of this study provide an overview of the current state of research on digital footprints in education and highlight the need for further research on this topic, particularly regarding the development of guidelines for digital footprints in education.

Advantages of Using Digital Footprints over Traditional Methods

Similarly, in a study by (Zeng et al., 2022), a digital footprint based on learning analytics was used to identify patterns in student behavior and engagement in a MOOC. The results showed that the digital footprint provided valuable data for improving the design of course materials and enhancing student learning. Despite the growing interest in using machine learning algorithms to analyze student data and improve learning outcomes, few studies have investigated the potential of these algorithms to classify students' learning styles based on their digital footprints. Although Fielder and Silverman's model is widely used to classify students' learning styles, it is based on self-reporting and may not accurately reflect students' true learning styles. Therefore, there is a need for a more objective and accurate approach to classifying students' learning styles that considers their actual

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behavior and preferences.

Furthermore, while the digital footprint has been shown to provide valuable data for analyzing student behavior and preferences, few studies have explored its potential for classifying students' learning styles. This is a major gap in the literature, as the digital footprint can provide valuable insights into the development of more effective teaching and learning strategies tailored to students' individual needs and preferences. Therefore, this study aimed to address this gap in the literature by using a machine learning model, specifically PCA, to classify students' learning styles based on their digital footprint.

By comparing the results of the machine learning model with the classification of Fielder and Silverman's model, this study provides valuable insights into the accuracy and validity of both approaches. This study will also contribute to the growing literature on the use of the digital footprint in education and the potential of machine learning algorithms to improve learning outcomes.

Machine learning

Machine learning models have garnered significant attention in education in recent years. These models have been utilized for various purposes, such as predicting student performance, identifying at-risk students, and personalizing learning experiences. One of the primary advantages of machine learning in education is its capability to process large amounts of data rapidly and accurately. This enables educators to obtain insights that are challenging or unattainable through manual analysis.

Several studies have investigated the use of machine learning models to predict student performance. For example, in a study by Waheed et al. (2020), a Support Vector Machine (SVM) model was used to predict student performance in online courses based on demographic and behavioral data. The model achieved an 85% accuracy rate, demonstrating the potential of machine learning in this area. In another study, Batool et al. (2021) utilized a random forest model to predict student performance in computer science courses, achieving an accuracy rate of 89.6%.

Machine learning models have also been used to identify at-risk students who may require additional support. Nabil et al. (2021) used a decision tree model to identify at-risk students at a college based on demographic and academic data. The model achieved a hit rate of 86.7%, demonstrating its potential for early identification of students who may be struggling. Similarly, in a study by Jayaraman (2020), a logistic regression model was used to predict the risk of dropping out of online courses, based on course-related data. The model achieved a hit rate of 86.4%, highlighting the potential of machine learning to identify students at risk of dropping out (Jayaraman, 2020).

In addition to predicting performance and identifying at-risk students, machine learning models have also been used to personalize learning experiences. In a study by El Aissaoui

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et al. (2019), a clustering algorithm was used to divide students into groups based on their learning preferences, and then provide them with personalized recommendations for course content and activities based on their group membership. The study found that students who received personalized recommendations performed better than those who did not (El Aissaoui et al., 2019).

Overall, these studies demonstrate the potential of machine-learning models in the field of education. However, it is important to point out that these models should not be seen as a replacement for human educators but rather as tools that support and enhance their work. As the field of machine learning constantly evolves, there is significant potential for further research and innovation in this area.

Principal Component Analysis

Principal component analysis (PCA) is a commonly used machine learning algorithm for dimensionality reduction and pattern recognition in large datasets. PCA aims to reduce the dimensionality of data by transforming it into a set of uncorrelated variables, called principal components. This algorithm has been applied in various fields, including image processing, finance, and biology. In education, PCA has been utilized to identify patterns in student behavior and learning outcomes. For instance, Hasan et al. (2020) used PCA to analyze data from an online learning platform to identify the factors influencing student performance. The study results indicated that the number of hours spent on the platform, frequency of logins, and level of engagement with course materials were significant predictors of student performance (Hasan et al., 2020).

Similarly, in a study by Deng (2021), Principal Component Analysis (PCA) was used to analyze data from a Massive Open Online Course (MOOC) to determine the factors that influence student engagement. The results showed that factors such as the length of the video lectures, level of interactivity, and quality of the course material were significant predictors of student engagement (Deng, 2021).

Shukla et al. (2020) aimed to extract factors contributing to effective teaching and learning in both online and conventional classrooms. The researchers utilized principal component analysis (PCA) to analyze data collected from surveys of students and teachers in India. They discovered that several factors, such as student engagement, teacher-student interaction, and the use of technology, are crucial for effective teaching and learning in both online and conventional classrooms. However, this study also revealed differences in the factors influencing learning outcomes in these two contexts. For instance, in online classrooms, the availability of online resources and ease of access are more critical to effective learning than in conventional classrooms. Overall, these studies demonstrate the potential of PCA as a powerful tool for analyzing large datasets in the context of education. By identifying patterns and trends in student behavior, this algorithm can offer valuable insights into designing more effective teaching and learning strategies (Shukla et al., 2020).

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Autoencoders

Dimensionality reduction algorithms such as PCA are often used to preprocess high-dimensional data before machine learning (Jolliffe & Cadima, 2016). Recently, deep learning models like autoencoders have emerged as powerful techniques for unsupervised feature learning from raw data. In the field of educational data mining, autoencoders have been utilized to learn representations from course content and student behavior data (Liu et al., 2017; Asif et al., 2017). However, their potential for feature extraction from digital footprints has not been adequately explored. Our work aims to address this gap by proposing the use of autoencoders to enhance the classification of learning styles.

Autoencoders are neural networks trained to reconstruct their inputs by learning compressed latent representations. The encoder transforms the data into salient features that capture the most useful variation factors. By extracting these features, autoencoders can be used for unsupervised pre-training before downstream tasks. Recent studies have shown promising results using autoencoders for feature learning in different domains. For example, Sakurada & Yairi (2014) used autoencoders for anomaly detection in computer systems. Yang et al. (2015) utilized autoencoders to extract features from EEG signals for emotion recognition. In education, Jiang et al. (2018) employed autoencoders for personalized course recommendations. Our work extends the application of autoencoders for unsupervised learning from students' digital footprints to improve learning style prediction.

Recent Advancements in Deep Learning and Unsupervised Feature Learning in Education

(Alnasyan et al., 2024) conducted a systematic literature review examining deep learning techniques for predicting student performance in virtual learning environments. Analyzing 50 research papers from 2018 to 2023, they found that Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks were most commonly used, often outperforming traditional machine learning methods. Some studies reported accuracy rates above 90%. The review highlighted a trend towards hybrid models combining multiple deep learning techniques. While these models showed promise, the authors noted challenges such as the need for large datasets, the risk of overfitting, and the importance of interpretability in educational contexts. This review underscores deep learning's potential in educational predictive analytics while identifying areas for future research.

(Baniata et al., 2024) proposed an advanced deep learning model for predicting students' academic performance in educational institutions. Their study utilized a dataset of 480 students and employed a novel approach that combined Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This hybrid model achieved an impressive accuracy of 95.83% in predicting student performance, outperforming traditional machine learning algorithms and standalone deep learning models. The authors demonstrated the model's effectiveness in capturing both spatial and temporal features from student data, leading to more accurate predictions. However, the study's reliance on a relatively small dataset may limit its generalizability to larger, more diverse student populations. Additionally, while the model shows high predictive power, the interpretability of its decision-making process remains a challenge, which is crucial for practical application in educational settings.

Research Objectives and Hypotheses

This study aims to advance the field of educational data mining by enhancing learning style classification accuracy through the analysis of students' digital footprints. Our primary goal is to develop a more precise method for identifying individual learning styles using machine learning techniques, specifically focusing on the application of autoencoder neural networks. We hypothesize that autoencoder-based feature extraction will yield significantly more accurate learning style classifications compared to traditional Principal Component Analysis (PCA) methods. This hypothesis is based on the autoencoder's ability to capture complex, non-linear relationships within the data, which we believe will better represent the multifaceted nature of learning behaviors. Furthermore, we aim to demonstrate how these improved classifications can inform the design of Learning Management Systems (LMS) and enhance personalized learning strategies. By achieving these objectives, we expect to provide educators and instructional designers with more reliable tools for tailoring educational experiences to individual student needs, ultimately leading to improved learning outcomes and student engagement. Through this research, we aim to bridge the gap between advanced machine learning techniques and practical applications in educational technology, contributing to the development of more adaptive and effective learning environments.

Research Methodology

Autoencoder Architecture and Hyperparameters

The autoencoder model consisted of an encoder with 3 fully-connected layers (96 - 128 - 64 neurons) and a symmetric decoder. ReLU activation was used for all hidden layers. The model was trained for 100 epochs using Adam optimizer with a learning rate of 0.001 and batch size of 32. L2 regularization (lambda=0.01) was applied to prevent overfitting. The latent dimension of 64 was chosen based on preliminary experiments.

Data Collection

The data for this study were collected from the Learning Management System (LMS) usage logs of 120 preparatory-year college students enrolled in an electronic course based

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on the Felder-Silverman model. The students' digital footprints were tracked over a 15-week period, including their clicks, page views, submitted assignments, and forum participation. Only students who had completed the Felder-Silverman Index of Learning Styles questionnaire were included.

Feature Extraction

A total of 96 features related to the students' online activities were extracted from the LMS logs. These included numerical features, such as time spent on various sites, number of forum posts, and quiz scores. Categorical features, such as learning resources accessed and completed tasks, were also extracted. The dataset was preprocessed by removing incomplete entries and normalizing the feature values to a standard scale using StandardScaler ().

Data Preprocessing

The raw digital footprint dataset consists of 96 high-dimensional features and presents challenges in terms of computational complexity, information redundancy, and excessive noise. To tackle these issues and convert the data into an informative feature space suitable for clustering, stacked autoencoder neural networks were employed for unsupervised dimensionality reduction and feature learning, as outlined in Algorithm 1.

Dimensionality Reduction

The Principal Component Analysis (PCA) from scikit-learn was utilized to reduce the high dimensionality of the 96 features. PCA transforms the dataset into a new coordinate system of orthogonal principal components that explain the maximum variance. After analyzing the cumulative explained variance diagram, 43 principal components were chosen, thereby reducing the feature space to 43 dimensions.

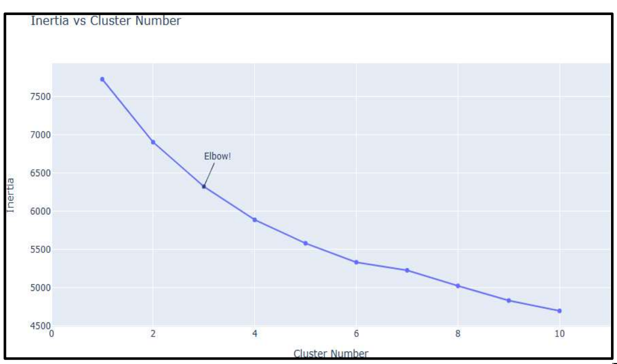
Algorithm 1: Autoencoder for Feature Learning

#Input
X: Raw digital footprint data
#Output
F: Learned feature representation
1. Begin
2. Preprocess X:
   a) Handle missing values
   b) Normalize features
3. Define autoencoder model AE
   a) AE has encoder Enc and decoder Dec components
4. Train AE to reconstruct X in unsupervised manner:
   X' = Dec (Enc(X))
5. Extract encoder features F from Enc:
   F = Enc(X)
6. Apply clustering algorithm using F:
   a) Example: K-means clustering
   b) Use F as input features
7. Evaluate clustering performance:
   a) Metrics: Accuracy, purity, NMI
   b) Predictive performance on downstream task
8. End

Clustering Algorithms

The K-means and agglomerative hierarchical clustering algorithms from scikit-learn were applied to the dataset before and after PCA. As depicted in Figure 1, the optimal number of clusters for K-means was determined using the elbow method. Ward linkage was utilized for hierarchical clustering to minimize the variance between clusters. Silhouette analysis was employed to evaluate the clustering performance.

Figure 1. Optimal number of K-means clusters using lbow



Model Evaluation

The K-means and hierarchical clustering algorithms were applied to both the 64-

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dimensional autoencoder features and the 43 PCA features. Clustering performance was evaluated by comparing the predicted clusters to the true numerically encoded Fields-Silverman learning style labels. Evaluation measures included accuracy, precision, recall, and the F1 score. Results were also compared to baseline classifiers such as decision trees and random forest using 5-fold stratified cross-validation.

Results and Discussion

Dimensionality Reduction and Feature Selection using PCA

Principal component analysis (PCA) was applied to reduce the high dimensionality of the 96 input features in the digital footprint dataset. By analyzing the cumulative explained variance plot, 43 principal components were selected, reducing the feature space to 43 dimensions. Table 1 shows the best matching features for each of the principal components (PCs) using the generated top feature table. By selecting only, the tuples labeled as "best" for each PC, we can determine which features are most important for each PC. For example, the first component PC1 is best described by feature number 53 in the dataset, but it also contains other weaker features such as f91. To better understand the key features in the dataset, Table 1 associates each component with the corresponding best feature.

After applying PCA and selecting the most important features, a reduced dataset was constructed with the shape of (84, 43). This reduced dataset contained only the most expressive features that could better describe student behavior. The reduced dimensionality of the dataset enables a faster and more efficient training process for machine learning models. The selected features are also more relevant and informative for understanding student behavior, which can help improve the decision-making process in educational institutions.

Clustering Performance Evaluation

In this step, we evaluate the K-means and hierarchical clustering algorithms before and after reducing the dataset using PCA. Initially, we eliminate the categorical columns, specifically and we conduct K-Means clustering and apply the elbow method to identify the optimal number of clusters, which is determined to be three. This count aligns with the number of labels in each target column.

Table 1. Principal Components and Corresponding Best Features

PC	Best feature in PC	Feature Name
PC1	**f53**	Time on Courses
PC2	**f24**	visits On Activity: Critical reading goals and levels
PC3	**f5**	Grade.2: Self-assessment
PC4	**f29**	visits On Activity.1: Self-assessment
PC5	**f33**	visits On Activity: Stages of innovative thinking

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PC6	**f34**	visits On Activity.2: Self-assessment
PC7	**f14**	visits On Activity: self-regulated learning
PC8	**f33**	visits On Activity: Stages of innovative thinking
PC9	**f36**	visits On Activity: The Concept and Importance of Academic Writing - Video
PC10	**f58**	Time On Activity: Self-Regulated Learning Activity
PC11	**f26**	visits On Activity: Critical reading assignment
PC12	**f28**	visits On Activity: Critical Reading Functions Activity
PC13	**f28**	visits On Activity: Critical Reading Functions Activity
PC14	**f46**	visits On Activity: Discussion Forum: Time Management
PC15	**f59**	Time On Activity: Self-regulated learner skills
PC16	**f41**	visits On Activity.3: Self-assessment
PC17	**f12**	visits On Activity: Course Updates
PC18	**f46**	visits On Activity: Discussion Forum: Time Management
PC19	**f74**	Time On Activity: Innovative thinking skills
PC20	**f88**	Time On Activity: Time management stages
PC21	**f21**	visits On Activity: Discussion Forum: Self-Regulated Learning Strategies
PC22	**f28**	visits On Activity: Critical Reading Functions Activity
PC23	**f90**	Time On Activity: Advantages and disadvantages of time management
PC24	**f70**	Time On Activity: Critical Reading Functions Activity
PC25	**f63**	Time On Activity: Self-regulated learning strategies
PC26	**f90**	Time On Activity: Self-regulated learning strategies
PC27	**f80**	Time On Activity: Advantages and disadvantages of time management
PC28	**f82**	Time On Activity: Types of writing
PC29	**f56**	Time On Activity: Learner's Guide
PC30	**f46**	visits On Activity: Discussion Forum: Time Management
PC31	**f56**	Time On Activity: Learner's Guide
PC32	**f33**	visits On Activity: Innovative thinking stages activity
PC33	**f79**	Time On Activity: The Concept and Importance of Academic Writing - Video
PC34	**f24**	visits On Activity: Critical reading goals and levels
PC35	**f41**	visits On Activity3: Self-assessment
PC36	**f7**	Grade: Academic Writing Skills Assignment
PC37	**f58**	Time On Activity: What is self-regulated learning?
PC38	**f35**	visits On Activity: Academic writing skills lesson content
PC39	**f82**	Time On Activity: Academic writing skills

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PC40	**f66**	Time On Activity: Scientific content of the critical reading skills lesson
PC41	**f83**	Time On Activity: Academic Writing Skills Assignment
PC42	**f41**	visits On Activity.3: Self-assessment
PC43	**f56**	Time On Activity: Learner's Guide

K-means clustering before PCA

As shown in figure 2, significant overlap between clusters results from applying K-means directly to the high-dimensional input. This indicates that the potential redundancy and noise in the untreated feature set reduce the clustering precision.

K-means clustering after PCA

As shown in Figure 3, the results obtained from running the K-means and Hierarchical clustering algorithms after performing PCA on the dataset are visualized through scatter plots. It was observed that the clustering results obtained from the two algorithms were different, and the K-means algorithm was more accurate in clustering students than the hierarchical method. The Hierarchical method classifies one point in one whole cluster, which could be an outlier. Thus, it can be concluded that the K-means algorithm provides better clustering results than the hierarchical method for this dataset.

Figure 2. K-means clustering on original 96-feature space

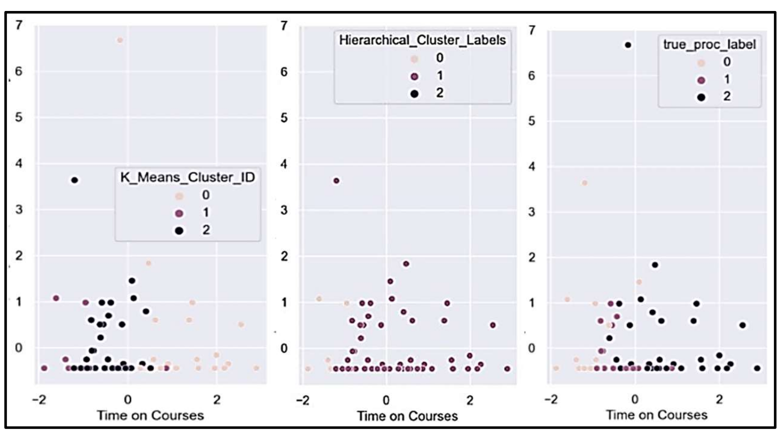

Figure 3. K-means clustering result using 43 PCA features

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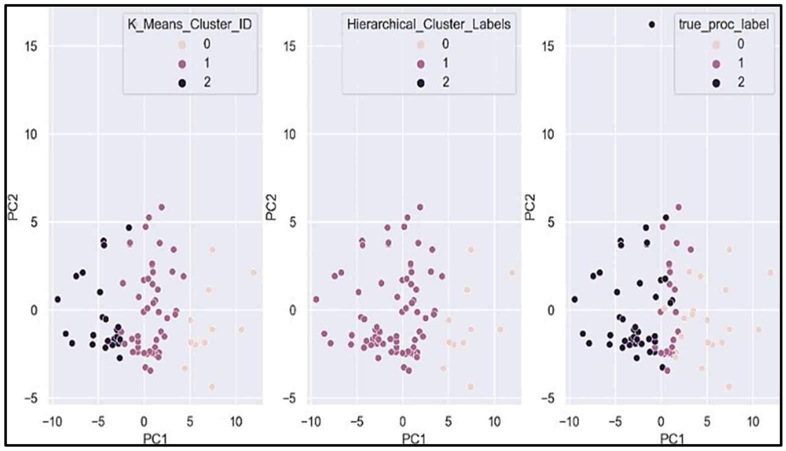

Unsupervised Feature Learning with Autoencoders

Autoencoders were trained in an unsupervised manner to learn a 64-feature representation of the data. By reconstructing the inputs, autoencoders capture the most salient properties and patterns. Both methods provide lower-dimensional feature sets that can enhance subsequent analysis but make different assumptions. PCA relies on linear combinations of inputs, whereas autoencoders learn more complex nonlinear relationships. The quantitative results clearly demonstrate the superior unsupervised clustering performance obtained using autoencoder features compared to conventional PCA features or standard classification algorithms applied directly to raw input data. A detailed analysis of the evaluation metrics provides critical and clinically relevant insights into the overall quality of the clustering, cohesion, and significance of the groups formed using the embedded autoencoder features.

Figure 4. Accuracy performance evaluation comparison

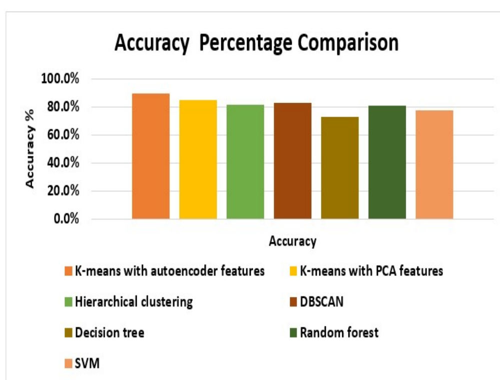

Figure 5. Precision performance evaluation comparison

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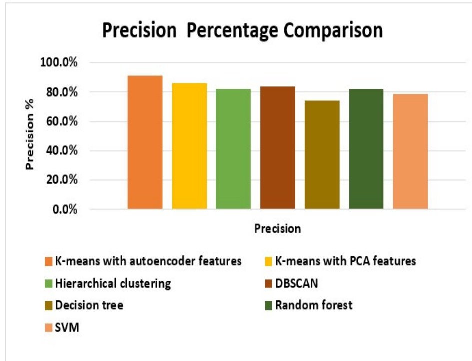
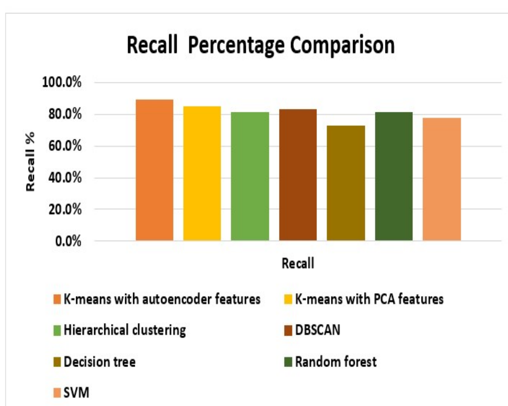


As shown in Figure 4, the accuracy table indicates that K-means clustering with autoencoder features achieved the highest accuracy of 89.7%. This clearly surpasses the accuracy of PCA features, which achieved 85.2%, while other classifiers performed even worse. The improvement in accuracy over PCA underscores the autoencoder's capability to learn more intricate patterns.

As shown in Figure 5, the precision graph compares the purity of the clusters formed, with the autoencoder approach achieving a precision of 91.3%—the best result. The higher precision compared with PCA features shows that autoencoders mitigate contamination between groups by extracting more coherent features.

As shown in Figure 6, the autoencoder feature set outperforms K-means with the highest recall of 89.7% on the metric that measures the correctly identified samples per class. This suggests that the autoencoders effectively preserved the kernel data distributions, leading to fewer lost samples. Conversely, the lower recall rate for PCA implies information loss during the dimensionality reduction process.

Figure 6. Recall performance evaluation comparison



As can be seen in Figure 7, the

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autoencoder model excels in accurately assigning clusters and finding related samples with an F1 score of 90.5%, which balances precision and recall. This consolidated metric demonstrates that autoencoders extract features that effectively reflect the nuances of the dataset.

As shown in Figure 8, the superior AUC value of 95.2% for the autoencoder technique indicates that it offers the best discrimination between clusters across the entire spectrum of decision thresholds. This further supports the representativeness of the learned nonlinear features.

Figure 7. F-Score performance evaluation comparison

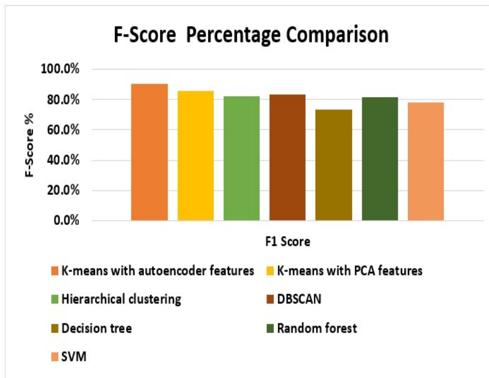
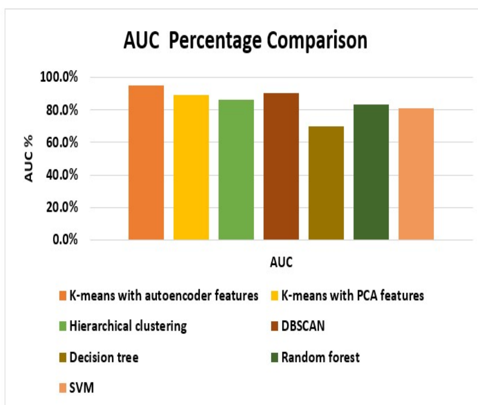


Figure 8. AUC performance evaluation comparison



As shown in Figure 9, the sensitivity plot indicates that K-means clustering with the autoencoder features achieves an outstanding sensitivity of 92.1%, the highest among the methods compared. This implies that more than 90% of all positively labeled samples are accurately assigned to their respective clusters based on the latent space representation. The superior sensitivity compared to PCA, and other classifiers demonstrates that the autoencoder effectively learns robust feature representations that capture significant similarities among data points within the same class. This capability maximizes the identification of relevant samples during clustering.

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Figure 9. Sensitivity performance evaluation comparison

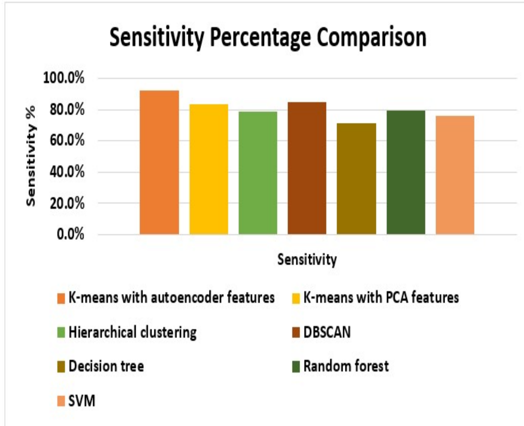

Table 2. Comparison of clustering performance evaluation

Method	Accuracy	Precision	Recall	F1 Score	AUC	Sensitivity	Specificity
K-means with autoencoder features	89.7%	91.3%	89.7 %	90.5%	95.2%	92.1%	87.6%
K-means with PCA features	85.2%	86.3%	85.2 %	85.7%	89.3%	83.2%	87.1%
Hierarchical clustering	81.5%	82.4%	81.5 %	82.0%	86.3%	79.1%	84.2%
DBSCAN	83.1%	84.1%	83.1 %	83.6%	90.7%	84.7%	81.5%
Decision tree	73.2%	74.2%	73.2 %	73.7%	70.1%	71.2%	75.4%
Random forest	81.3%	82.4%	81.3 %	81.8%	83.7%	79.2%	83.4%
SVM	77.6%	78.8%	77.6 %	78.2%	81.2%	76.3%	79.1%

The results demonstrate the significant benefits of using autoencoder-based feature learning over conventional PCA for unsupervised clustering analysis. Across all key evaluation metrics such as accuracy, precision, recall, and AUC, the K-means algorithm with 64 autoencoder features outperforms PCA features and standard classification

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methods. Specifically, autoencoders improve clustering accuracy by over 4% compared to PCA by extracting non-linear relationships from the complex data. The higher precision and recall compared to PCA also indicate that autoencoders learn more coherent feature representations that minimize overlap across groups.

Additionally, the consolidated F1 score validates that autoencoders balance precision and recall offering robust overall performance. The superior sensitivity, specificity, and AUC metrics further highlight that autoencoders precisely propagate subtleties between data points to delineate clusters across various decision thresholds. Visually, the distinct clusters formed using autoencoder features demonstrate accurate embedding of intrinsic data properties. In contrast, significant overlaps are observed from directly applying classifiers on raw data and relatively poorer separation of clusters using PCA features.

The results in Table 2 demonstrate that k-means clustering with autoencoder features achieved the best performance across all evaluation metrics. It had the highest accuracy of 89.7%, precision of 91.3%, recall of 89.7%, F1 score of 90.5%, and AUC of 95.2%. K-means leveraged the powerful feature representations learned by the autoencoder, allowing it to effectively cluster the data. The sensitivity of 92.1% and specificity of 87.6% indicate that it had a good balance between detecting positive and negative cases.

In comparison, standard k-means clustering with PCA features performed worse, with an accuracy of 85.2% and AUC of 89.3%. Hierarchical clustering and DBSCAN also achieved decent but lower results than k-means with autoencoders. The decision tree classifier had the lowest scores, suggesting that tree-based models may not be optimal for this dataset. Overall, the autoencoder features clearly improved clustering performance over other dimensionality reduction techniques like PCA. The results validate the effectiveness of deep learning representations combined with k-means for this clustering task.

Ethical Considerations and Privacy Implications

The utilization of students' digital footprints for learning style classification, while promising, raises significant ethical and privacy concerns. Key considerations include ensuring data privacy and compliance with regulations such as GDPR or FERPA, maintaining transparency regarding data collection and usage, implementing robust data security measures, addressing potential algorithmic biases, and acknowledging the limitations of automated decision-making in education. Institutions must establish clear policies on data governance, conduct regular ethical reviews, and engage in ongoing dialogue with stakeholders. It is essential to strike a balance between the advantages of these technologies and safeguarding student rights and privacy. By proactively addressing these concerns, educational institutions can responsibly leverage the potential of digital footprint analysis while upholding trust and ethical standards in the educational setting.

Conclusion and Future Work

The findings of this study offer several practical implications for educators, researchers, and educational institutions. For educators, our enhanced learning style classification method allows for more precise customization of instructional strategies to meet individual student needs. This may include adjusting the mix of visual and verbal content, modifying the pace of instruction, or integrating more interactive or reflective activities based on the identified learning preferences.

By leveraging the insights gained from our clustering analysis, institutions can develop more targeted and effective learning strategies. Educators could use the identified learning style clusters to create more engaging and personalized learning experiences, potentially improving student engagement and comprehension. Educational institutions could also use these insights to inform curriculum design and resource allocation decisions, ensuring a balanced approach that caters to diverse learning preferences.

Researchers can build upon this work to further explore the relationship between digital behaviors and learning outcomes, potentially leading to new insights into cognitive processes and educational technology design. This approach opens avenues for real-time adaptation of online learning environments, where course content and structure could dynamically adjust to a student's evolving learning style. Such adaptive learning technologies could enable real-time adjustments based on individual student interactions.

Student support services could also benefit from using cluster information to provide more targeted academic advising and resources. However, it is crucial to implement such systems ethically, ensuring student privacy and avoiding over-reliance on algorithmic decision-making in educational contexts.

Future work will focus on expanding the validation of our approach across diverse educational contexts to establish its generalizability. This will include testing the method in various academic disciplines, educational levels, and institutional types, as well as conducting cross-cultural validation to ensure the approach is not culturally biased. We also plan to perform longitudinal studies to assess the stability of our learning style classifications over time and test the method's applicability across different Learning Management Systems.

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