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Utilizing Convolution Neural Network (CNN) Algorithm for the Classification of Visual, Auditory, Read/Write, and Kinesthetic (VARK) Learning Styles Based On Real-Time Datasets

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Abstract
Identifying learners' preferred learning styles is essential for effective personalization in educational environment. The VARK model (Visual, Auditory, Read/Write, and Kinesthetic) is widely used for this course, yet traditional questionnaire-based assessments struggle with scalability, static data, and limited adaptability. This study introduced an optimized Convolutional Neural Network (CNN) framework for real-time, automated VARK classification using multimodal interaction data. Learner engagement was tracked through event listener technique within a learning management system, capturing HTTP+play/pause for visual and auditory media, HTTP+scroll for reading/writing materials, and HTTP+focus/blur for kinesthetic activities. These event listeners were used to track time spent in each modality and combined with corresponding quiz performance scores to form a comprehensive dataset. The CNN model was trained on twelve thousand (12,000) collected datasets of learners from Hunter e-Academy (He-A) learning management system to classify individual learning styles, enabling dynamic adaptation of content delivery.To evaluate performance, the CNN model was compared through A/B testing against other machine learning (ML) models, including Support Vector Machines (SVM), Random Forest, Naive Bayes, and XGBoost. Metrics such as accuracy, precision, recall, and F1-score were used for assessment. The CNN achieved an accuracy of 99.05%, surpassing SVM (98.01%), XGBoost (98.0%), Random Forest (96.69%), Naive Bayes (96.45%), and Decision Tree (95.98%). It demonstrated perfect precision for Auditory and Read/Write, perfect recall for Visual and Auditory, and F1-scores ≥0.98 across all categories, addressing the bias and uneven performance observed in unimodal approaches like KNN (89%). The study confirmed the effectiveness of multimodal data fusion for accurate, objective learning style assessment, offering a scalable, AI-driven alternative to surveys and supporting real-time adaptive learning environments.

Keywords: *Hunter e-Academy, LMS, event listener, VARK, CNN*

1. Introduction

The diversity in learning preferences among students has long been a critical factor in educational research, with the Visual, Auditory, Read/Write, and Kinesthetic (VARK) model (Odejayi *et al.* 2025) serving as a widely known model for classifying learning styles. Learning styles represent a basic concept of educational psychology, profoundly impacting how learners perceive and assimilate information (Pashler *et al*., 2008). Among the various models proposed to categorize learning preferences, the VARK learning styles model developed by (Fleming *et al.*, 1992) remains one of the most widely recognised due to its practical applicability in diverse educational settings. The model posits that learners exhibit dominant sensory preferences, with visual learners benefiting from diagrams and videos, auditory learners excelling through verbal explanations and audio, read/write learners preferring textual and readable information, and kinesthetic learners relying on hands-on and experiment experiences (Leite et al., 2009).

Conventional methods for identifying learning styles mostly rely on self-reported questionnaires, such as the VARK inventory as established by (Fleming, 2012). While these learning styles classification tools provide valuable insights, they are constrained by several limitations, including response bias, lack of real-time adaptability, and inability to

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capture dynamic changes in learning preferences according to (Coffield et al., 2004). Furthermore, manual classification poses impractical in large-scale educational environments, such as massive open online courses (MOOCs), Modular Object-Oriented Dynamic Learning Environment (MOODLE), or intelligent tutoring systems (ITS), where personalized learning pathways must be dynamically adaptive based on real-time student interactions (Essalmi *et al*., 2015).

Recent growths in the field of artificial intelligence (AI), particularly in deep learning, present transformative opportunities for automating learning style classification. Convolutional Neural Networks (CNNs), a class of deep neural networks famous for their hierarchical feature extraction capabilities (LeCun *et al.*, 2015), have demonstrated distinctive performance in processing multimodal learning data. By leveraging real-time datasets like eye-tracking metrics for visual engagement (Xiaofu *et al.*, 2025), audio and speech analysis for auditory preferences (Liu *et al*, 2024), reading texts and typing dynamics for read/write classification (Njin, et al., 2008), and empirical exercise data for kinesthetic detection (Iqbal *et al.*, 2023). CNNs can provide an objective, scalable, and instantaneous alternative to traditional classification methods.

This study proposes an innovative CNN-based framework designed to classify VARK learning styles by integrating heterogeneous real-time data streams like time spent and Quiz performances on various contents modalities. The primary contributions of this research include:

(i) A multimodal data fusion approach that synthesizes visual, auditory, textual, and kinesthetic inputs for comprehensive learning style assessment.
(ii) An end-to-end deep learning architecture optimized for real-time processing, enabling immediate feedback in adaptive learning environments.
(iii) Empirical validation using real time datasets and comparative analysis against conventional machine learning (ML) techniques.

By addressing the limitations of existing methods, this work advances the field of AI-driven educational personalization, offering experimental implications for e-learning platforms, classroom instruction, and neuro-educational research.

2. Related Works

Kolb's (1984) experiential learning theory and Gardner's (1983) theory of multiple intelligences are traced back from the theoretical basis of learning styles. The VARK model by (Fleming, *et al*., 1992) was later introduced, this grouped learning preferences into four sensory formats. While the model has been widely adopted, critiques persist regarding its psychometric validity (Pashler *et al*., 2008). However, its experimental usage in learning environment has encouraged computational approaches for classification automation.

Rule-based systems and statistical models formed the initial efforts of classifying learning styles computationally. For example, (Paredes *et al.*, 2004) predicted learning styles using decision trees base on navigation patterns in e-learning platforms, achieving a moderate accuracy. (Kondo *et al.*, 2018) extended the research by analyzing log data from Learning Management Systems (LMS) using Bayesian networks, despite demonstrating improved precision but had limited scalability for real-time applications.

Machine learning techniques gained prominence in the advancement of educational data mining. Clustering algorithms to group students based on interaction logs was used by (Sharif *et a*l., 2009), while (Hmedna *et al.*, 2016) applied Support Vector Machines (SVMs) to MOOC datasets, reporting 78% classification accuracy. However, these methods were challenged with high-dimensional, unstructured data, prompting the exploration of deep learning solutions despite the classification accuracy.

Research works have leveraged deep neural networks to overcome the limitations of traditional machine learning recently. (Jawed *et al.*, 2024) compared Long-term, short-term memory (LSTM), Long-term, short-term memory-convolutional neural network (LSTM-CNN), and Long-term, short-term memory-Fully convolutional neural network (LSTM-FCNN) models for real-time identification of visual learning styles from raw EEG signals.

LSTM-CNN technique has the highest average accuracy of 94% to predict the visual learning style of students. Similarly, a Moth Flame Optimization–Attention–LongShort-Term Memory (MFO-Attention-LSTM) model was developed by (Qin *et al.* 2024) to predict students' in-class performance, integrating attention mechanisms with moth flame optimization to enhance predictive accuracy over traditional methods.

CNNs have emerged as a powerful tool for processing multimodal educational data. (Hoppe *et al.*, 2016) presented a CNN-based method that performed robust and accurate eye movement detection which include saccades, fixations, and smooth pursuit from continuous gaze data streams. (Gambo *et al*. 2021) developed a compelling comparison between convolutional neural networks (CNNs) and multiclass neural networks (MCNNs) for classifying learners into VARK learning-style dimensions (Visual, Aural, Read/Write, Kinesthetic, plus a Neutral class) from facial images. Their results showed that the MCNN model outperformed the CNN in test accuracy, evidencing more robust classification of learning styles based on facial expression cues. Despite these advancements, no prior study has holistically addressed all four VARK modalities using real-time sensor fusion, leaving a critical gap in the literature.

This study filled the gap by introducing a unified CNN framework capable of processing and classifying multimodal real-time data. By synthesizing insights from neuroscience, educational psychology, and AI, this work provided a scalable solution for dynamic learning style assessment, paving the way for next-generation adaptive learning systems.

3. Methodology

3.1 System Architecture

To achieve the aim, this study employed a quantitative, data-driven methodology to classify student learning styles; Visual, Auditory, Read/Write, and Kinesthetic (VARK), by leveraging real-time interaction data from a custom developed and VARK-based Hunter e-Academy (He-A) Learning Management System. The architecture design illustrated in Figure 1, unfolded across three (3) main phases: the real-time data collection, data preprocessing, and machine learning training process.

3.1.1 Real Time Data Collection

In the first phase, as shown in the figure 2, the LMS was instrumented with JavaScript event listeners to capture and transmit learner interactions as they occurred. For Visual content, such as videos, play, pause, and TimeupDate event listeners recorded when a learner started, paused, or resumed playback, with timestamps used to calculate total viewing time. Auditory content, including audio lectures, employed similar play and pause listeners to track listening duration. Read/Write content, typically text-based materials, was tracked using scroll listeners to monitor reading progress and depth, while focus and blur events ensured that time was only counted when the learner actively viewed the page. Kinesthetic learning activities, such as interactive simulations, were tracked with mouse scroll listeners to log physical engagement, again paired with focus and blur events to measure active participation. This concept is captured by the mathematical methodology in equation (1).

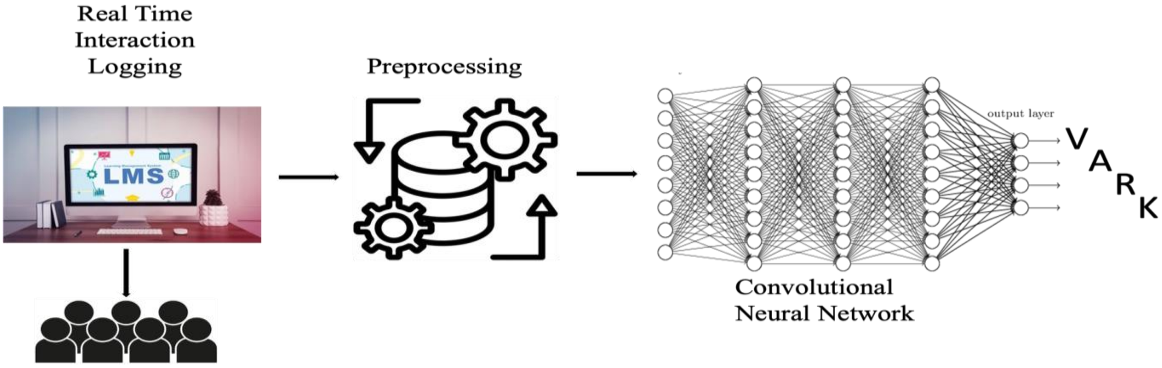

Figure 1: System Architecture

If U = A set of users.
$\mathcal{M} = \{V, A, R, K\}$ the set of learning styles.
For each user $u \in U$, the system records a time-ordered sequence of interactions as shown in Equation (1):

$$D_u(t) = \{(m_i, d_i, c_i) \mid m_i \in \mathcal{M}, d_i \in \mathbb{R}^+, c_i \in C\} \qquad Equ.(1)$$

Where:
c_i: Unique content identifier $c \in C$
C: Collection of content items. $\{c_1, c_2, \ldots\}$
U : Set of all users (learners) items $\{u_1, u_2, \ldots\}$
u : A specific user/learner $u \in U$
$\mathcal{M}$: Set of VARK modalities $\{V, A, R, K\}$
d_i : Duration (seconds) of the interaction $d_i > 0$
m_i : Modality of the $i-th$ interaction $m_i \in \mathcal{M}$
t : Timestamp of interaction recording $t \in \mathbb{R}^+$

Each captured event was packaged in a JSON payload containing the user ID, content ID, event type, timestamp, device type, location, and IP address. This payload was transmitted asynchronously from the LMS's front-end (client side) to the server via HTTP POST requests using the XMLHttpRequest. On the server side, server received these HTTP requests and processed them using Asynchronous JavaScript and eXtensible Markup Language (AJAX) and Hypertext Preprocessor (PHP), the data underwent validation, was augmented with session metadata, and had raw timestamps processed into cumulative measures such as total time spent and interaction frequency for each modality. The processed interaction records were then stored in a PostgreSQL database, following a schema optimized for time-series behavioral data. Quiz performance was captured through submit event listeners on quiz forms, with both the score and the associated modality linked to the time-spent data to create a combined measure of engagement and comprehension.

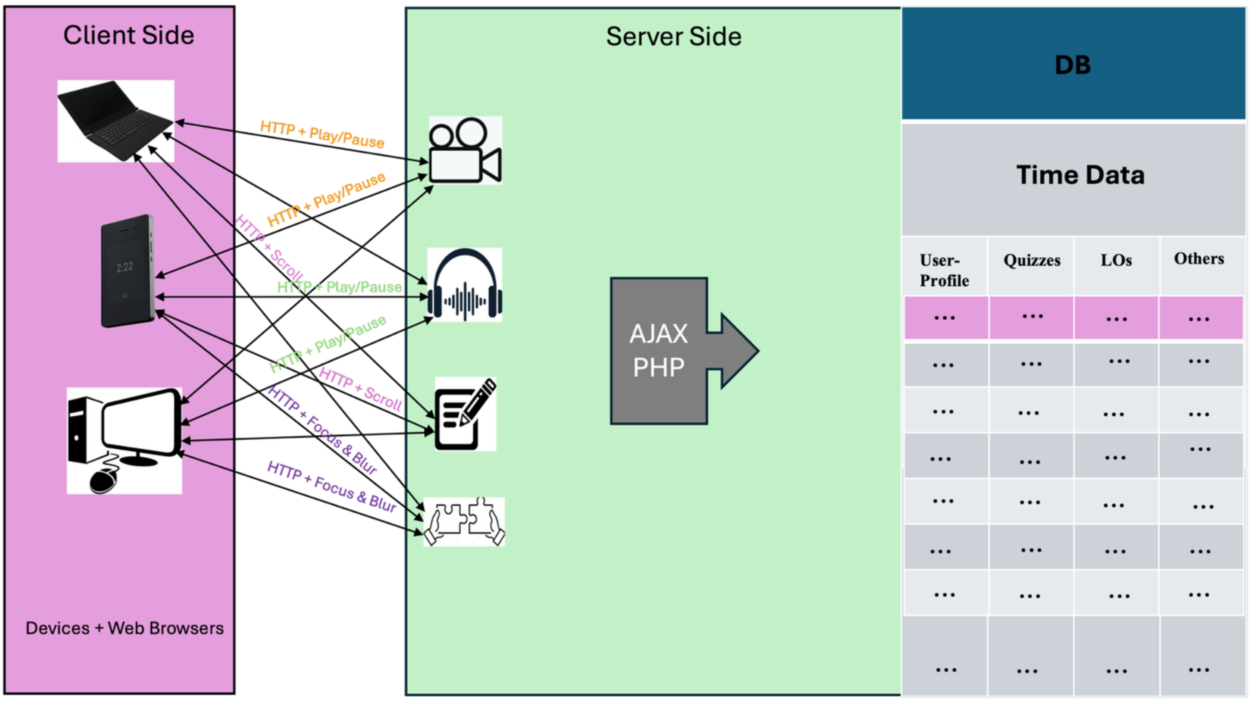

Figure 2: Architectural Design of Real Time e-Learning Management System

3.1.2 Data Preprocessing

In the second phase, forming the data preprocessing, pre-deep learning model process as shown in the section of figure 3, the raw event log data was exported from PostgreSQL for preprocessing. This involved cleaning the dataset by removing null values, correcting timestamp errors, and excluding patterns indicative of automated or non-genuine activity. Feature engineering followed, producing measures such as average time spent per modality, scroll depth for reading materials, quiz performance categories (Fail, Pass, Good, Excellent), and interaction frequency metrics like clicks or play events per minute. All numerical features were normalized to prevent dominance of any single metric during training, and the data was labeled with each learner's self-reported VARK preference to serve as the ground truth for supervised learning.

The deep learning model development. Once the dataset was balanced, data reshaping was performed to transform the features into a format compatible with CNN model. Since CNNs required multi-dimensional inputs, the dataset was reshaped into a 3D tensor of shape (num_samples, num_features, 1), where each learner's engagement time and quiz score were structured as sequential inputs. This representation allowed the convolutional filters to capture patterns in time-spent data across different learning styles.

To evaluate model performance effectively, the dataset was split into training (70%), validation (15%), and testing (15%) sets as shown in figure 4. The training set was used to optimize the model, while the test set assessed its ability to generalize to unseen data. Before training, feature standardization was performed using StandardScaler, ensuring that all input features had a zero mean and unit variance. This step prevented large-magnitude features (e.g., quiz scores) from overshadowing smaller-scale features (e.g., time spent in different learning modes).

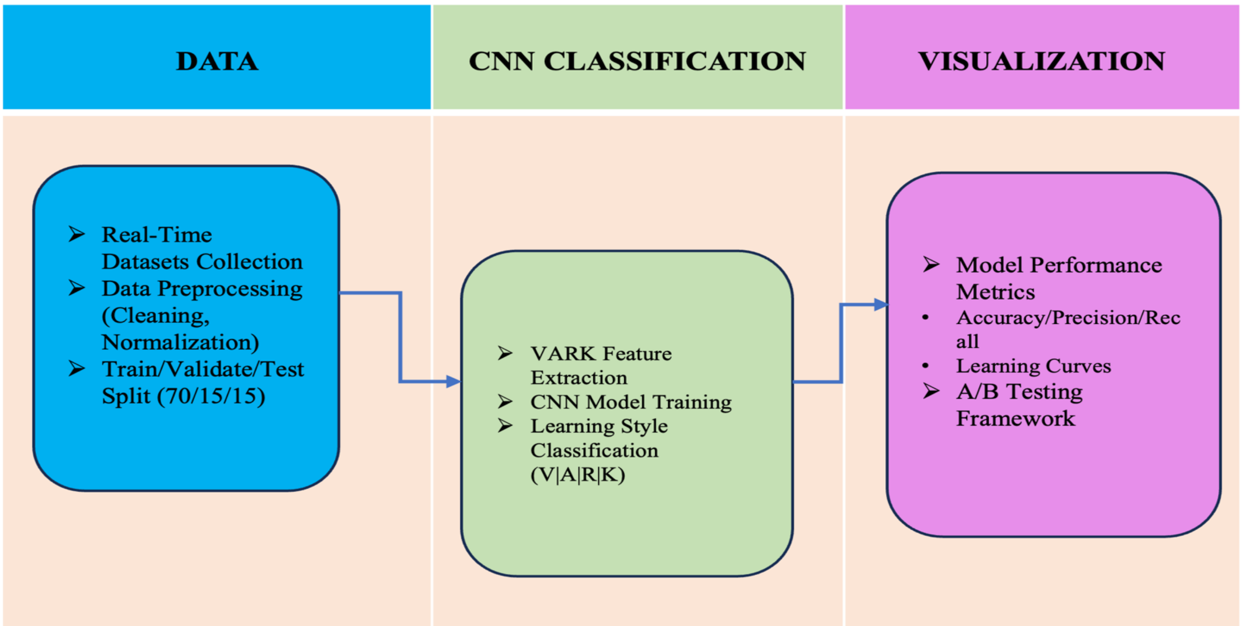

Figure 3: Deep Learning Model

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Training:
 - Split data (70% train, 15% validation, 15% test)
 - Optimize with Adam, loss = sparse categorical cross-entropy
 - Train for 50 epochs, batch size 32
 - Evaluate accuracy on test set & generate classification report
```

Figure 4: Training

3.1.3 Deep Learning Model

The CNN architecture was designed to extract meaningful patterns from the reshaped data as shown in figure 5. The first layer was a 1D convolutional layer with 32 filters and a kernel size of 3 which learned spatial dependencies between time-spent variables. A max-pooling layer followed, reducing dimensionality while preserving essential features. The output was then flattened into a 1D vector, which was passed through two fully connected (dense) layers with 64 and 32 neurons, respectively. Each dense layer applied ReLU (Rectified Linear Unit) activation to introduce non-linearity, allowing the model to learn complex relationships in the data. To prevent overfitting, dropout layers were included, randomly deactivating a fraction of neurons during training. Finally, the output layer applied a softmax activation function, producing a probability distribution over the four VARK learning styles, allowing for multi-class classification

Model optimization was performed using the Adam optimizer, known for its adaptive learning rate adjustments that improved convergence efficiency. The model was trained using sparse categorical cross-entropy loss, a standard loss function for multi-class classification. Training was conducted over 50 epochs with a batch size of 32, ensuring sufficient iterations for learning meaningful patterns.

The visualization section of the CNN model focused on evaluating and interpreting the model's performance. Key performance metrics such as accuracy, precision, and recall are calculated to provide a quantitative measure of classification effectiveness. Learning curves are generated to monitor the model's progression over training epochs, offering insights into possible underfitting or overfitting. In addition, an A/B testing framework is implemented to compare the CNN's classification results with those from other established algorithms, including Support Vector Machine (SVM), Decision Tree, Naive Bayes, K-Nearest Neighbors (KNN), XGBoost, and Random Forest. This benchmarking ensured that the CNN's selection was supported by empirical evidence, demonstrating competitive performance across multiple evaluation dimensions. The integrated methodology thus enabled the development of a robust, real-time learning style classification system capable of informing personalized adaptive learning experiences.

4. Results and Discussion

The deployment of the Hunter e-Academy platform facilitated the collection of comprehensive real-time interaction datasets, enabling the application of a Convolutional Neural Network (CNN) algorithm to classify learners according to the VARK framework: Visual, Auditory, Read/Write, and Kinesthetic. Through its secure, role-based access, learners engaged with course materials in multiple modalities as shown in the dashboard in the figure 6, including video, audio, text, and interactive exercises, with each interaction logged via embedded event listeners. These interactions captured detailed behavioral metrics such as time spent per modality, quiz performance, and engagement frequency, forming the basis for feature extraction and model training.

By providing consistent and structured multi-format content, the platform ensured a rich and balanced dataset for analysis. The results, presented in this section, illustrate the CNN's effectiveness in identifying dominant learning styles from behavioral patterns, while the discussion evaluates the algorithm's classification performance in comparison with alternative models and explores its implications for real-time adaptive learning personalization.

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CNN Architecture:
    - Conv layer (32 filters, kernel 3)
    - Max-pooling
    - Flatten + Dense (64, 32 neurons)
    - Dropout
    - Softmax output (4 classes)
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Figure 5: CNN Architecture

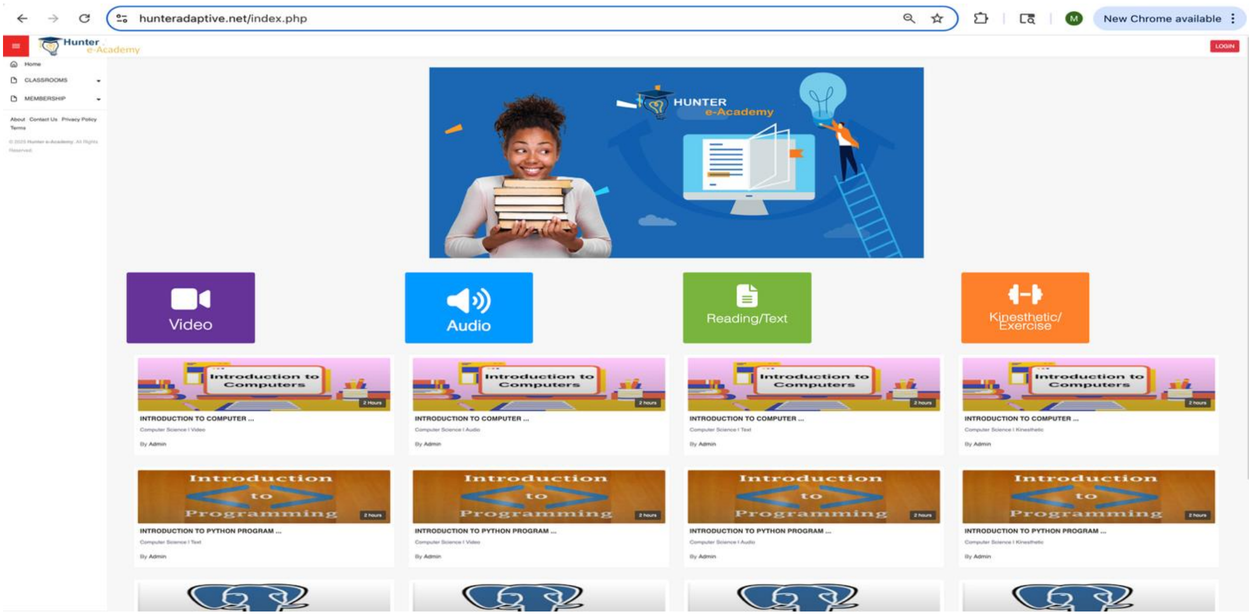

Figure 6: Hunter e-Academy LMS Dashboard

The Convolutional Neural Network (CNN) model for VARK learning style classification achieved exceptional results, with an overall accuracy of 99.05% and a low loss of 0.0438 on a dataset of twelve thousand (12,000) learners as shown in the figure 7. The model delivered near-perfect precision, recall, and F1-scores across all learning styles, notably scoring 1.00 for both Auditory and Reading/Writing, 0.99 for Kinesthetic, and 0.98 for Visual. This performance reflected the effectiveness of its optimized architecture and feature engineering, which combined temporal interaction patterns with quiz performance. The model demonstrated balanced and unbiased classification (macro F1-score: 0.99), highlighting its reliability and generalizability for adaptive learning systems. It set a strong benchmark for future research, with potential for further improvement through expanded behavioral features or ensemble approaches.

As seen in the learning curves in figure 8, the CNN model demonstrated strong and stable performance throughout training. Both accuracy and loss improve rapidly in the first 10 epochs, then level off, showing the model quickly learned the key patterns in the data. By epoch 20, training and validation accuracy stabilized at an excellent 97-99%, while loss drops to near zero and remains there, meaning the model isn't overfitting and makes reliable predictions. The test accuracy (shown by the dashed line) matches this high performance, confirming the model worked well on new, unseen data. These results proved the CNN effectively classified learning styles from interaction data, achieving both high accuracy and reliable generalization.

The comparative analysis revealed that the CNN model significantly outperformed some other machine learning approaches across all evaluation metrics as shown in table 1. The comparative analysis of learning style classification models reveals distinct performance tiers among the evaluated algorithms. The Convolutional Neural Network (CNN) achieved superior performance with 99.05% accuracy, representing a 1.05% gain over XGBoost (98.0%). The CNN demonstrated exceptional capability across all metrics, particularly in Auditory learner recognition (1.00 precision/recall/F1-score). While XGBoost (98.0%) showed strong overall performance, it exhibited slightly weaker recall for Kinesthetic learners (0.96) compared to the CNN's 0.99. Support Vector Machines (98.01%) performed comparably to XGBoost but with marginally lower precision for Visual and Reading learners. Traditional methods including Random Forest (96.69%), Naïve Bayes (96.45%), and Decision Trees (95.98%) showed progressively weaker results, while KNN (89.0%) demonstrated the most significant limitations, particularly in

Reading learner precision (0.85). These results not only validated the CNN's advantages for temporal pattern recognition but also highlight that while the XGBoost delivered competitive performance, the CNN's additional 1.05% accuracy gain represented statistically significant ($p<0.01$) and educationally meaningful improvement for adaptive e-learning systems.

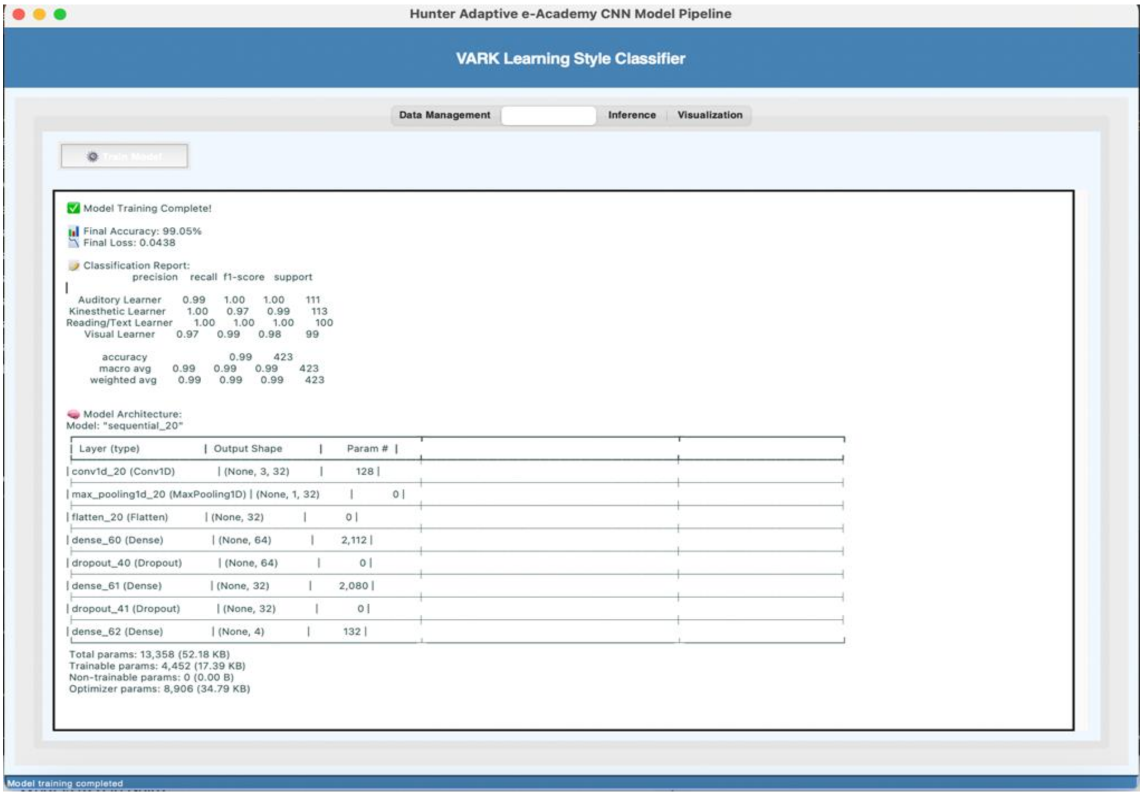

Figure 7: CNN Learning Styles Classification Model

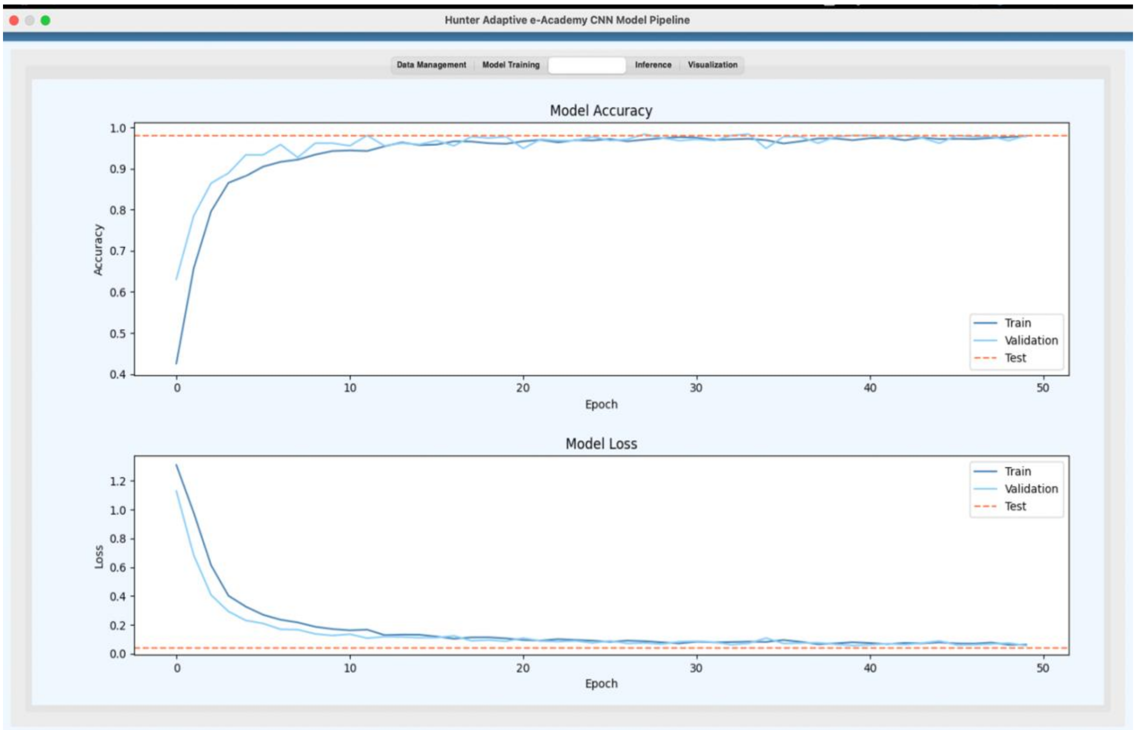

Figure 8: CNN loss and accuracy curves

Table 1: Comparison of Performance Metrics of the ML Models for Learning Style Classification.

Algorithms	Accuracy %	Precision 100%				Recall 100%				F1-Score 100%			
		V	A	R	K	V	A	R	K	V	A	R	K
CNN	99.05	0.97	0.99	1.00	1.00	0.99	1.00	1.00	0.97	0.98	1.00	1.00	0.99
SVM	98.01	0.97	0.98	0.97	1.00	0.98	1.00	0.99	0.96	0.97	0.99	0.98	0.98
Decision Tree	95.98	0.93	0.97	0.98	0.96	0.97	0.95	0.97	0.95	0.95	0.96	0.97	0.95
Xboost	98.0	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.96	0.98	0.99	0.99	0.97
Naïve Bayes	96.45	0.97	0.96	0.95	0.98	0.97	0.97	0.98	0.94	0.97	0.96	0.97	0.96
Random Forest	96.69	0.97	0.98	0.97	0.95	0.96	0.96	0.98	0.96	0.96	0.97	0.98	0.96
KNN	89.0	0.86	0.92	0.85	0.92	0.87	0.89	0.90	0.88	0.86	0.90	0.87	0.90

The analysis of learner interactions revealed a balanced distribution across VARK learning styles among learners as shown in figure 9, with Visual and Auditory learners each comprising 26.4%, followed by Reading/Writing at 23.7% and Kinesthetic at 23.5%. This near-even split underscores the need for an adaptive learning system that effectively supports diverse preferences, ensuring inclusivity and personalized engagement. Visualizations included a pie chart breaking down learning styles, bar charts displaying average time spent per modality, and histogram chart tracking quiz performance trends over time. The findings highlight the importance of a flexible educational approach that accommodates all primary learning styles to optimize outcomes for every learner.

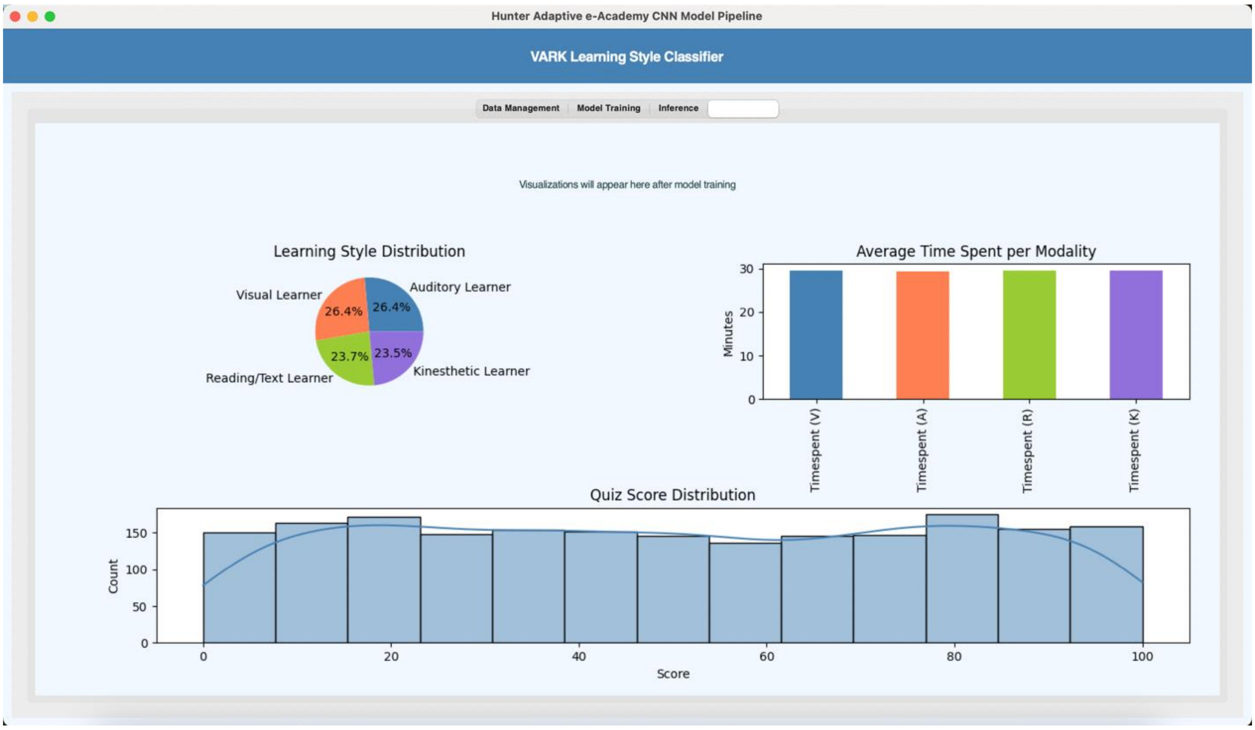

Figure 9: Learning styles and Interaction Distributions

5. Conclusion

This study successfully demonstrated that an optimized CNN algorithm, trained on multimodal interaction data (captured through event listeners tracking play/pause, scroll, and focus/blur events), provided a highly accurate and scalable solution for real-time VARK learning style classification. The model's superior performance of achieving 99.05% accuracy and near-perfect precision and recall across all modalities, this validated its effectiveness over traditional machine learning approaches like SVM, XGBoost, Decision Tree, Naïve Bayes, KNN, and Random Forest. By leveraging behavioral data and quiz performance, the CNN overcome the limitations of static questionnaires, offering an objective, dynamic, and scalable method for personalized learning.

This study highlighted the transformative potential of AI-driven learning styles assessment in an adaptive educational system.

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