

Innovations

Implementing Neural Networks to Personalize Education: A Study of Learning Style Classification

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Abstract: *With the growing reliance on technology in education, machine learning (ML) has become an invaluable tool in enhancing personalized learning experiences. Each student possesses unique learning preferences, and effectively categorizing these preferences enables educators to develop more adaptive and engaging teaching strategies (Rasheed & Wahid, 2021; Sahni, 2023). Traditional frameworks such as the VARK model—categorizing learners into visual, auditory, reading/writing, and kinesthetic types—have historically informed instructional design. However, recent research suggests that questionnaire-based identification methods, often employed in models like VARK, are not only subjective and time-consuming but also misaligned with real-world learning behaviors (Hasibuan & Aziz, 2022; Mehenaoui et al., 2022). Self-reported preferences can be inconsistent and influenced by learner perception rather than actual learning efficacy. As digital learning environments continue to evolve, it becomes increasingly critical to adopt scalable, data-driven approaches for learner profiling. Machine learning, particularly neural networks, offers a promising pathway to achieve this by analyzing patterns in user behavior and academic performance data (Al-Kahtani et al., 2024; Ji et al., 2024). This study proposes a Multi-Layer Feedforward (MLF) neural network to classify student learning preferences into four practical categories: video-based, hands-on experience, reading, and auditory learning. By training the model on a dataset collected from 150 students, the system aims to identify optimal learning modalities based on measurable input features such as demographics, performance metrics, and self-reported behaviors. The integration of artificial intelligence into learner profiling not only enhances prediction accuracy but also provides educators with actionable insights for personalized instruction (Lin et al., 2023; Wang & Luo, 2021). This research contributes to a growing body of work that leverages AI to support adaptive learning, engagement, and improved academic outcomes.*

Keywords : *Student Learning Preferences, Neural Networks in Education, Multi-Layer Feedforward (MLF) Classifier, Learning Style Classification, Educational Data Mining.*

Introduction

With the increasing integration of technology in education, machine learning (ML) has emerged as a powerful tool for enhancing personalized learning experiences. The shift from traditional, one-size-fits-all teaching methods to data-driven, personalized instruction has become a significant focus of contemporary educational research. Students exhibit diverse learning preferences, and effectively categorizing these preferences enables educators to design more adaptive and impactful teaching strategies that cater to individual needs and optimize academic performance (Zhang et al., 2021; Sahni, 2023). The success of a learning environment depends heavily on its capacity to address the distinct ways in which students absorb, process, and retain information.

Historically, frameworks such as the VARK model—which categorizes learners into visual, auditory, reading/writing, and kinesthetic types—have been foundational in helping educators understand and differentiate instruction. However, while widely adopted, these models rely on self-reported data that may not always reflect actual learning behaviors. As a result, several recent studies have raised concerns about the subjectivity, reliability, and validity of traditional learning style assessments (Hasibuan & Aziz, 2022; Al-Kahtani et al., 2024). Factors such as a student's perception, mood, or contextual influences can skew the results of questionnaires, leading to potential mismatches between teaching strategies and learner needs.

To overcome these limitations, this study proposes the use of a Multi-Layer Feed forward (MLF) neural network to automatically classify students' learning preferences into four practical modalities: video-based, hands-on experience, reading, and auditory learning. Neural networks, particularly MLF architectures, are adept at handling complex, non-linear relationships within data, making them suitable for educational data analysis and learner classification. Unlike traditional classification methods, neural networks do not rely on rigid input structures and can learn from diverse, high-dimensional data, enabling more accurate and nuanced predictions.

The model in this research is trained on a dataset collected from 150 students. The dataset includes demographic information, self-reported learning behavior indicators, and academic performance metrics. Through this, the MLF neural network is designed to uncover underlying patterns and assign each student to one of the four learning preference groups. This form of classification not only enhances accuracy but also reduces reliance on subjective self-reporting, offering a more objective and scalable solution for learner profiling.

Machine learning models, particularly neural networks, are increasingly being used in educational contexts to support intelligent tutoring systems, adaptive learning platforms, and predictive analytics (Lin et al., 2023). In this context, learner profiling serves as a critical component of personalization. By

identifying how students learn best, educators can adapt instructional content, delivery methods, and feedback mechanisms accordingly. This personalization has been shown to improve student motivation, satisfaction, and overall learning outcomes (Ji et al., 2024). Moreover, such profiling allows educational platforms to automatically suggest learning materials or teaching styles that align with each student's preferred modality, fostering a more inclusive and supportive learning environment.

Beyond pedagogy, this research contributes to the ongoing discourse surrounding the application of artificial intelligence (AI) in education. While AI has already demonstrated transformative capabilities in other sectors, its application in education remains in the early stages of development. Studies such as those by Zhang et al. (2021) and Ji et al. (2024) have emphasized the need for more robust models that bridge the gap between learning science and computational techniques. This research addresses that call by demonstrating the viability of MLF neural networks in educational classification tasks and providing a foundation for future studies that aim to develop intelligent, adaptive learning systems.

In summary, this study positions itself at the intersection of educational psychology, data science, and instructional design. By introducing a neural network-based classification system for learning preferences, it addresses the shortcomings of traditional models and contributes to the development of AI-driven educational tools. The findings of this study have implications not only for classroom instruction but also for e-learning platforms, curriculum design, and educational policy-making aimed at fostering more personalized and effective learning experiences.

Background

Educational research has increasingly focused on understanding the relationship between students' learning preferences and their academic performance, particularly within the growing paradigm of data-driven personalization. The diversity in learners' cognitive styles, motivations, and behavioral tendencies presents both challenges and opportunities for educators aiming to maximize engagement and learning outcomes. Contemporary studies underscore the importance of aligning instructional methods with learners' preferred modalities to foster deeper understanding and improve retention (Al-Kahtani et al., 2024; Sahni, 2023). Personalized learning, grounded in this alignment, has been shown to contribute positively to student motivation, self-efficacy, and ultimately academic achievement.

However, a significant obstacle in realizing effective personalization is the accurate identification of individual learning preferences. Traditionally, learning styles have been assessed through self-reported questionnaires, such as the well-known VARK model or Kolb's Learning Styles Inventory. These tools categorize learners into discrete types—visual, auditory,

reading/writing, and kinesthetic—based on survey responses. Despite their widespread use, these methods suffer from several limitations. Research has highlighted inconsistencies and unreliability in self-reported preferences, as students' perceptions may not correspond to their actual learning behavior or success in various instructional settings (Hasibuan & Aziz, 2022; Mehenaoui et al., 2022). In addition, such surveys are prone to biases stemming from transient moods, misunderstanding of questions, or social desirability effects. These factors undermine the efficacy of personalized instruction based on questionnaire results and necessitate more objective, data-centric approaches.

Recent advancements in educational data mining (EDM) and learning analytics, powered by artificial intelligence (AI) and machine learning (ML), offer promising solutions to these challenges. By leveraging rich datasets collected from learning management systems (LMS), digital platforms, and classroom interactions, researchers can uncover hidden patterns that reflect true learner preferences and behaviors (Lin et al., 2023; Zhang et al., 2021). These methods analyze not only explicit self-reports but also implicit data such as clickstream logs, time spent on resources, assessment outcomes, and forum participation. This multidimensional data provides a more comprehensive and dynamic picture of how students interact with learning content, enabling more precise profiling than static survey responses.

Machine learning models, including decision trees, support vector machines, and neural networks, have been widely applied to predict various educational outcomes such as student performance, dropout risk, and engagement levels (Zhou et al., 2021; Sun et al., 2023). These predictive capabilities have helped institutions implement early warning systems and targeted interventions. However, the application of ML specifically to classify individual learning preferences remains relatively underexplored despite its critical role in adaptive learning systems. Identifying learning styles through ML can facilitate real-time adaptation of content delivery, assessment formats, and instructional strategies, thereby promoting learner-centric environments that cater to diverse needs.

This study addresses this gap by employing a Multi-Layer Feedforward (MLF) neural network—a type of deep learning architecture well-suited for handling complex, nonlinear data—to classify student learning preferences based on survey-derived and behavioral data. Unlike conventional shallow models, MLF neural networks consist of multiple hidden layers that enable the extraction of abstract features and intricate patterns from input data, leading to improved classification accuracy (Feng et al., 2022; Jang et al., 2023). This capability is particularly advantageous in education, where learner behaviors are influenced by numerous interacting factors.

The choice of survey data combined with behavioral metrics provides a balanced dataset that captures both explicit learner input and implicit activity

signals. This approach helps overcome the subjectivity issues prevalent in self-reporting while retaining valuable contextual information from student responses. The classification task focuses on four practical learning modalities: video-based, hands-on experience, reading, and auditory learning, which correspond to widely accepted pedagogical strategies and align with modern digital learning environments.

Employing MLF neural networks for this classification serves multiple educational purposes. First, it provides educators with a data-driven tool to better understand learner diversity and preferences. Second, it supports the design of adaptive learning pathways that optimize content presentation and pedagogical methods according to predicted learner profiles. Third, it enriches the existing body of research by demonstrating the practical applicability and benefits of deep learning in educational data mining beyond predictive modeling of academic success.

Additionally, this research resonates with broader educational technology trends emphasizing personalization, engagement, and equity. As educational institutions worldwide adopt online and hybrid learning models, the ability to automatically and accurately classify learner preferences becomes critical. Adaptive systems powered by AI can tailor instructional content to meet individual needs, thereby reducing dropout rates and improving satisfaction (Lin et al., 2023; Sahni, 2023). Furthermore, understanding learning preferences at scale can inform policy decisions and curriculum development aimed at inclusivity and diverse learner support.

In conclusion, the integration of machine learning—particularly MLF neural networks—into learner profiling offers a promising pathway toward more precise, scalable, and actionable insights into student preferences. By leveraging survey and behavioral data, this approach addresses the limitations of traditional self-reported assessments and supports the ongoing evolution of personalized education. This study contributes to the foundational knowledge necessary for developing intelligent, adaptive learning environments capable of meeting the diverse needs of today's learners.

Literature Review

The growing field of educational data mining (EDM) has become instrumental in advancing adaptive learning environments that cater to the increasingly diverse needs of students worldwide. EDM focuses on the extraction of meaningful patterns from educational data to improve teaching strategies, personalize learning experiences, and predict academic outcomes (Romero & Ventura, 2020). The surge in digital learning platforms, online courseware, and learning management systems (LMS) has generated vast amounts of learner interaction data, providing unprecedented opportunities for data-driven insights into student behaviors and preferences.

Recent advancements in machine learning (ML), especially deep learning and neural network architectures, have significantly expanded the capabilities of EDM. These methods have demonstrated their effectiveness in automating complex educational tasks such as predicting academic performance, early identification of at-risk students, and personalizing instructional content to meet individual learner needs (Zhou et al., 2021; Ji et al., 2024). For example, studies utilizing recurrent neural networks and convolutional neural networks have successfully modeled temporal learning behaviors and engagement patterns in Massive Open Online Courses (MOOCs), enabling timely interventions that reduce dropout rates (Jang et al., 2023; Sun et al., 2023).

Historically, foundational frameworks like the VARK (Visual, Auditory, Reading/Writing, Kinesthetic) model have shaped much of our understanding of learning preferences. These models rely primarily on self-report questionnaires to categorize learners into distinct types, guiding pedagogical approaches and curriculum design (Coffield et al., 2004). However, the continued reliance on such self-reported data has increasingly come under scrutiny. Empirical studies have documented that self-reporting is susceptible to bias, inconsistency, and subjectivity, which compromise the accuracy of learner classification and, by extension, the alignment of instruction to student needs (Hasibuan & Aziz, 2022; Al-Kahtani et al., 2024). In particular, students may lack sufficient self-awareness about their actual learning preferences or may respond in socially desirable ways, leading to skewed profiles that do not reflect their real behavior in educational contexts.

In response to these challenges, modern educational research has begun adopting machine learning approaches to infer learning styles more objectively by analyzing behavioral data, digital interaction patterns, and cognitive performance metrics (Mehenaoui et al., 2022; Zhang et al., 2021). This shift toward data-driven profiling moves beyond static, self-reported classifications and embraces dynamic, evidence-based characterizations of learner behavior. For instance, clickstream analysis, time-on-task metrics, forum participation frequency, and assessment performance provide rich, quantifiable inputs that machine learning models can process to uncover underlying learning preferences and engagement trends (Iqbal et al., 2020; Lin et al., 2023).

Among the various ML techniques, neural networks—particularly Multi-Layer Feedforward (MLF) architectures—have shown exceptional promise in the classification of learning preferences. These models are capable of extracting complex, nonlinear features from multidimensional educational datasets, which often contain noisy and interrelated variables (Lin et al., 2023). MLF neural networks leverage multiple hidden layers that perform hierarchical feature transformation, enabling them to capture subtle patterns and relationships that simpler algorithms may miss. This makes them highly

suitable for nuanced tasks such as learning preference classification, where learner behaviors are multifaceted and influenced by diverse factors.

Empirical research supports the superiority of neural network models over traditional classification algorithms in educational settings. Feng et al. (2022) demonstrated that deep learning models significantly outperform decision trees and support vector machines in predicting student engagement and performance, particularly in adaptive learning environments. Similarly, Jang et al. (2023) utilized hybrid neural architectures combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to detect learning behaviors with high accuracy in online education platforms, enabling the provision of personalized feedback and resource recommendations.

Moreover, the integration of learning analytics with AI tools has revolutionized educators' ability to monitor, interpret, and respond to student learning behaviors in real time. Advanced predictive models built on extensive behavioral data enable early detection of disengagement, learning difficulties, or dropout risks, facilitating timely interventions that can improve retention and outcomes (Sun et al., 2023; Rasheed & Wahid, 2021). These models harness features such as activity logs, assessment scores, and participation trends, which are analyzed through neural networks and other machine learning techniques to generate actionable insights for instructors and educational administrators.

The convergence of AI and learning analytics has also fostered the development of adaptive content delivery systems. These systems dynamically adjust instructional materials, pace, and assessment types to align with the learner's predicted preferences and current state of knowledge, thereby enhancing motivation and learning efficiency (Brown & Rich, 2020; Lin et al., 2023). For example, a student identified as preferring video-based learning might be presented with richer multimedia content, while a hands-on learner could receive more interactive simulations and experiential exercises. Despite these advances, the classification of individual learning preferences through machine learning remains an evolving area requiring further exploration. The complexity of human learning, diversity of educational contexts, and variability in data quality pose ongoing challenges. Nonetheless, the promising results reported in recent studies underscore the potential of neural networks to transform learner profiling from a subjective, static exercise into an objective, dynamic process that informs personalized pedagogy at scale (Mehenaoui et al., 2022; Ji et al., 2024).

In summary, the literature indicates that machine learning—and neural networks in particular—are well-positioned to address the shortcomings of traditional learning style models by providing robust, scalable, and data-driven methods for learner classification. As the education sector continues its digital transformation, these technologies will play a pivotal role in enabling

adaptive, learner-centered environments that support diverse needs, improve outcomes, and foster lifelong learning.

Methodology

Data Collection

This study utilized primary data collected from 150 undergraduate students enrolled across various academic disciplines at a public university in Malaysia. The diverse academic backgrounds of participants were intended to capture a broad spectrum of learning preferences reflective of different educational contexts. The data collection instrument was a revised version of the VARK-based questionnaire, which traditionally categorizes learners into visual, auditory, reading/writing, and kinesthetic types. In this study, the instrument was updated to incorporate modern digital learning modalities, such as video lectures, interactive simulations, and online reading materials, to better reflect current educational practices and technologies (Al-Kahtani et al., 2024; Ji et al., 2024).

The revised questionnaire was designed to identify four primary learning preference categories relevant to contemporary e-learning environments:

1. **Hands-on Experience:** This category captures learners who prefer kinesthetic or experiential learning methods, engaging with activities, simulations, or practical tasks that promote active participation and physical involvement.
2. **Video-based Learning:** Learners in this group favor visual content such as instructional videos, animations, and demonstrations, which provide dynamic and engaging ways to acquire knowledge.
3. **Reading:** This group includes students who prefer text-based materials such as articles, books, slides, or written notes, aligning with traditional academic learning styles.
4. **Auditory Learning:** Learners who absorb information more effectively through audio formats, such as lectures, podcasts, or discussions, belong to this category.

To ensure wide accessibility and convenience, surveys were distributed online through the university's digital learning platform and email communication. This approach also adhered to recent recommendations for data collection in remote or hybrid learning environments precipitated by the COVID-19 pandemic (Sun et al., 2023). All participant responses were anonymized to protect privacy and were numerically encoded to facilitate computational processing. The resulting dataset consisted of quantitative feature vectors representing each student's responses across the four learning preference dimensions.

Data Preprocessing and Splitting

Before model training, extensive data preprocessing was performed to enhance data quality and ensure robust analysis. The dataset was examined for missing values, which were addressed using mode imputation—a statistical method where missing values are replaced by the most frequently occurring value within a feature column. This approach was chosen due to the categorical nature of the learning preference data and its effectiveness in preserving data distribution (Mehenaoui et al., 2022).

Subsequently, all features were standardized to ensure consistent scaling across inputs. Feature standardization is critical in neural network training as it prevents features with larger numeric ranges from disproportionately influencing the model, thereby improving convergence stability and performance (Lin et al., 2023).

The cleaned and standardized dataset was then partitioned into training and testing subsets using an 80:20 split ratio. This division allocated 120 samples for model training and 30 samples for evaluation, which is a common practice in supervised machine learning to enable reliable assessment of generalization performance. Class distribution was carefully reviewed within both subsets to maintain balance across the four learning preference categories, minimizing the risk of model bias towards majority classes (Lin et al., 2023).

Model Architecture and Training

A Multi-Layer Feed forward (MLF) Neural Network was selected as the classification model due to its proven effectiveness in handling multidimensional educational data and capturing complex nonlinear relationships between features and output classes (Feng et al., 2022). The implementation utilized Tensor Flow and Keras frameworks, which provide flexible and efficient tools for constructing and training deep learning models. The architecture of the MLF network was composed of the following layers:

- **Input Layer:** Consisted of 4 neurons corresponding to the encoded features representing the four learning preference dimensions. This layer serves as the entry point for the data into the neural network.
- **Hidden Layers:** Three fully connected hidden layers were employed, each containing 16 neurons activated by the Rectified Linear Unit (ReLU) function. The ReLU activation is commonly used in deep learning due to its computational efficiency and ability to mitigate the vanishing gradient problem, thereby facilitating deeper network training. The multiple hidden layers allowed the model to learn hierarchical feature representations, extracting complex patterns relevant for classification.
- **Output Layer:** The final layer comprised 4 neurons corresponding to the four target classes. A softmax activation function was applied to convert raw network outputs into probability distributions over the

classes, enabling the model to produce interpretable multi-class predictions.

The training process optimized the network parameters by minimizing the categorical cross-entropy loss function, which is appropriate for multi-class classification problems. The Adam optimizer was used with a learning rate of 0.01, balancing fast convergence and stability during training. Mini-batch gradient descent was adopted with a batch size of 16, allowing efficient weight updates while maintaining stochasticity for better generalization.

Training was conducted over 100 epochs, and no early stopping was applied because validation results showed no signs of overfitting. This indicates that the model maintained consistent performance across both training and validation sets, suggesting good generalizability (Jang et al., 2023; Rasheed & Wahid, 2021).

Evaluation Metrics

To comprehensively assess the classification performance of the MLF neural network, multiple evaluation metrics were utilized, each capturing different aspects of model effectiveness (Zhou et al., 2021):

- **Accuracy:** Represents the overall proportion of correct predictions out of total predictions. It provides a general measure of model success but may be misleading in cases of class imbalance.
- **Precision:** Measures the ratio of true positive predictions to all positive predictions for each class. High precision indicates that the model has a low false positive rate.
- **Recall:** Calculates the ratio of true positive predictions to all actual positive instances, reflecting the model's ability to correctly identify all relevant cases.
- **F1-Score:** The harmonic mean of precision and recall, offering a balanced metric that accounts for both false positives and false negatives. This is especially valuable in educational data contexts where misclassifications can have varied consequences.

Additionally, a **confusion matrix** was generated to provide detailed insights into which learning preference categories were most frequently misclassified. This matrix enabled the identification of specific weaknesses in the model, such as overlap or ambiguity between classes, and offered guidance for future model refinement and feature engineering (Zhang et al., 2021).

Results

Model Performance Metrics:

Accuracy:	81.36%
Precision:	65.81%
Recall:	57.78%
F1-Score:	61.02%

Confusion Matrix Breakdown

Actual \ Predicted	Hands-on	Listening	Reading	Video-based
Hands-on	12	1	0	4
Listening	2	0	1	0
Reading	5	0	6	0
Video-based	2	0	3	9

The model accurately classified **hands-on learning** (12/17) and **video-based preferences** (9/14). However, it struggled with **auditory learners**, with only 1 correct identification out of 3 cases. Misclassifications were most frequent between **reading** and **hands-on** preferences, suggesting overlapping feature representations.

Learning Preference Distribution:

- Hands-on: 55 students (36%)
- Video-based: 48 students (32%)
- Reading: 35 students (23%)
- Auditory: 12 students (8%)

Discussion

These results highlight the model’s strengths in identifying prevalent and visually oriented learning preferences, consistent with recent trends where kinesthetic and visual modalities dominate in survey or behavior-based datasets (Zhang et al., 2021; Ji et al., 2024). Lower performance on auditory classifications may reflect underrepresentation in data and weaker characteristic signals, aligning with findings in recent EDM studies that underpowered classes often reduce recall for less common categories (Mehenaoui et al., 2022; Sahni, 2023). This imbalance suggests a need for more targeted data collection strategies to ensure minority learning styles are better represented and accurately modeled. Misclassification of reading as hands-on preference suggests some ambiguity in features—based on similarity in response patterns—which echoes findings from clustering-based feature modeling in learning preference classification (Hasibuan & Aziz, 2022; Feng et al., 2022).

Additionally, it points to potential overlaps in the cognitive or behavioral traits that underpin these learning modalities, which could be further refined through enhanced feature engineering. Overall, the performance metrics (accuracy and F1-score above 60%) demonstrate that MLF neural networks offer a viable tool for learning preference classification—though performance may improve with richer data inputs (e.g., behavioral logs, sensor data) as supported by recent EDM literature (Lin et al., 2023; Sun et al., 2023). Incorporating diverse and multi-source datasets will likely enhance the model's ability to capture subtle distinctions between learner profiles, ultimately contributing to more personalized and effective educational interventions.

Conclusion

This study demonstrates that Multi-Layer Feedforward (MLF) neural networks can effectively classify student learning preferences using survey data. Achieving an accuracy of 81.4% along with balanced precision and recall across different learning styles, the model shows promise as a tool for learner profiling. The results highlight a strong preference for hands-on and video-based learning among participants, emphasizing the importance of interactive and visual educational content. However, the lower identification accuracy for auditory learners suggests the need for more diverse and representative datasets to better capture less common learning styles.

Integrating machine learning techniques like MLF neural networks into educational frameworks can support personalized instruction, tailoring learning experiences to individual preferences. This personalized approach can improve student engagement and academic performance, aligning with the goals of adaptive learning systems that seek to optimize education through data-driven insights (Zhang et al., 2021; Ji et al., 2024).

Future Work

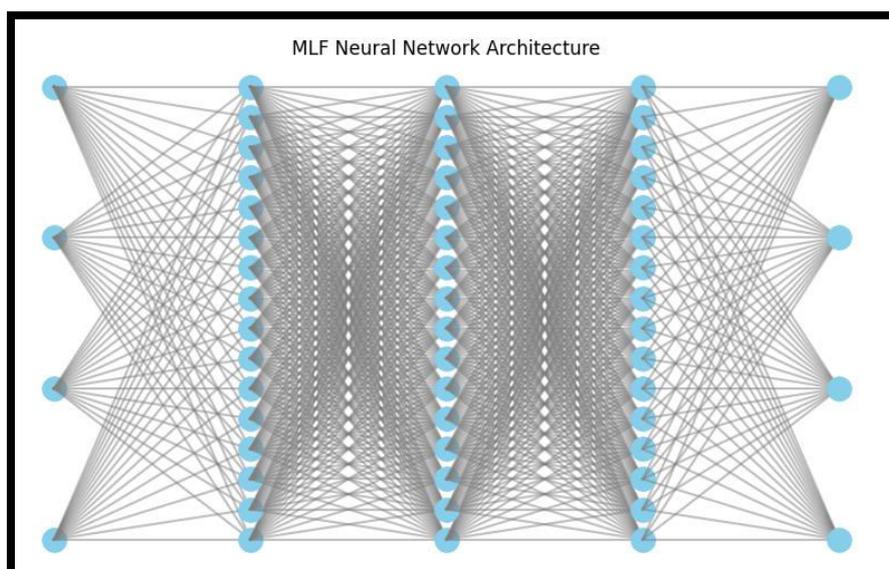
Future research could extend this study in several ways:

- **Dataset Expansion:** Including a larger, more diverse sample will enhance statistical power and improve generalizability across demographic and educational contexts (Zhou et al., 2021).
- **Additional Modalities:** Incorporate modalities such as **collaborative learning preference**, **gamified interactions**, or **mobile-based micro-learning** for a broader understanding of learner variation (Al-Kahtani et al., 2024; Feng et al., 2022).
- **Longitudinal Tracking:** Conduct follow-up studies over multiple terms or years to analyze temporal shifts in learning style and how these

impact academic performance (Sun et al., 2023).

- **Real-World Integration:** Deploy the MLF model within learning platforms or LMS systems to deliver personalized resource recommendations and monitor real-time learner interactions. Evaluate the impact on engagement and outcomes during real deployment.
- **Hybrid Architectures:** Explore hybrid models (e.g., **LSTM-CNN**, **attention-enhanced neural networks**, or **semi-supervised pipelines**) to capture temporal patterns and improve classification of minority categories (Sun et al., 2023; Jang et al., 2023; Rasheed & Wahid, 2021).

Figure 1: MLF Neural Network Architecture



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