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A Multi-Agent Smart Autonomous System for Adaptive Student Profiling in Personalized Learning

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Abstract — In order to facilitate dynamic customization in contemporary learning environments, this study introduces a Smart Autonomous System for Adaptive Student Profiling. To create constantly changing student profiles, the suggested architecture incorporates a variety of educational data sources, such as academic achievement, behavioral patterns, cognitive traits, environmental data, social interactions, and emotional indications. To handle missing data, the system uses KNN-based imputation Convolutional Neural Networks (CNNs) for emotion identification, Principal Component Analysis (PCA) for feature reduction, and XG Boost for academic risk prediction and student profile. A Deep Q-Network (DQN)-based reinforcement learning method that modifies suggestions and interventions based on learner needs enables autonomous decision-making. A hybrid recommendation engine also facilitates optimum learning paths and individualized material distribution. Real-time profiling, ongoing monitoring, proactive intervention, and adaptive feedback mechanisms are made possible by the framework's implementation within a multi-agent architecture. Learner engagement, academic achievement, and early detection of at-risk kids have all improved, according to experimental evaluation utilizing benchmark educational datasets. The findings show that the suggested approach is reliable, scalable, and successful in facilitating intelligent, customized learning environments.

Keywords— Adaptive Student Profiling, Personalized Learning Systems, Multi-Agent Architecture, Autonomous Decision-Making, Educational Data Mining

I. INTRODUCTION

The integration of intelligent technologies into education has transformed traditional learning environments into adaptive and data-driven systems. Personalized learning has emerged as a dominant paradigm for improving student engagement and academic performance by tailoring instructional content, pace, and strategies according to individual learner characteristics. Recent studies confirm that artificial intelligence enables adaptive learning experiences by analyzing student behavior, preferences, and performance in real time, leading to improved learning outcomes and engagement levels [1].

Despite these advancements, existing systems predominantly rely on static student models and limited data sources, which restrict their ability to capture the dynamic and multi-dimensional nature of learning processes. Effective personalized learning requires the integration of multi-source data and intelligent decision-making mechanisms to deliver accurate and timely interventions [2].

To address these challenges, this paper presents a fully implemented Smart Autonomous System for Adaptive Student Profiling that performs continuous profiling using multi-source data, including academic, behavioral, cognitive, contextual, and emotional attributes. The system leverages advanced artificial intelligence techniques and a multi-agent architecture to enable real-time adaptation, autonomous decision-making, and personalized recommendation generation [3].

Recent advancements in AI-driven learning systems further validate the effectiveness of such integrated frameworks in enhancing educational outcomes and supporting adaptive learning environments [4]. The proposed approach aligns with recent findings that emphasize the importance of intelligent, data-driven systems in achieving scalable and efficient personalized education [5].

II. RELATED WORKS

Recent advancements in artificial intelligence and educational data mining have significantly strengthened personalized learning systems by enabling dynamic adaptation, multi-source data integration, and intelligent decision-making. Modern research focuses on combining academic, behavioral, cognitive, contextual, and emotional parameters to build comprehensive student models that improve engagement, performance, and early risk detection. These studies confirm that AI-driven systems outperform traditional approaches by offering real-time adaptability, predictive analytics, and scalable personalization. The following literature highlights key contributions in this domain, emphasizing diverse methodologies and validated outcomes.

L. I. Sakri et al. [6] investigated AI-based recommendation systems in e-learning environments, integrating academic performance and behavioral interaction data to personalize content delivery. Their study demonstrated that incorporating learner activity patterns significantly improves recommendation accuracy and student engagement. The system effectively analyzed clickstream data and learning preferences to adapt content dynamically. Experimental results showed increased course completion rates and improved learner satisfaction.

A. M. Vieriu et al. [7] analyzed AI-driven adaptive learning systems focusing on academic and cognitive parameters such as performance scores and learning pace. Their model dynamically adjusted content difficulty based on real-time student progress. The study confirmed that adaptive mechanisms significantly enhance knowledge retention and academic performance. The system also reduced learning gaps by continuously updating student profiles.

K. I. Vorobyeva et al. [8] explored AI-supported personalized learning using natural language processing and machine learning techniques. Their work incorporated behavioral, contextual, and engagement-related features to enhance instructional delivery. The study highlighted that integrating multiple data sources improves system responsiveness and personalization accuracy. Results indicated improved student satisfaction and more effective learning pathways.

F. Malekpour et al. [9] developed an AI-based personalized learning framework that integrates academic and engagement parameters for higher education systems. Their model used predictive analytics to identify at-risk students and recommend targeted interventions. The system achieved high accuracy in performance prediction and improved student retention rates. The findings validated the importance of early risk detection mechanisms.

S. B. Panwale et al. [10] evaluated AI-based language learning systems incorporating cognitive and behavioral parameters such as error rates and retry behavior. Their model dynamically adjusted learning strategies based on student responses. The results demonstrated significant improvements in language proficiency and learning speed. The study emphasized the role of adaptive feedback in enhancing learning outcomes.

A. Fortuna et al. [11] conducted a comprehensive review of AI-driven personalized learning systems, focusing on multi-source data integration including academic, behavioral, and contextual information. Their findings confirmed that hybrid AI models significantly improve scalability and efficiency. The study also highlighted the importance of continuous learning and real-time adaptation. The results showed improved system performance across diverse educational settings.

M. S. Elhoseny et al. [12] proposed an intelligent learning framework integrating emotional and behavioral data using deep learning techniques. Their model utilized facial expression analysis to detect student engagement and affective states. The system improved personalization by adapting content based on emotional feedback. Experimental validation showed enhanced engagement and reduced dropout rates.

L. V. Mulaudzi et al. [13] analyzed AI adoption in education from a multi-parameter perspective, including social interaction and contextual learning behavior. Their study emphasized collaborative learning and peer interaction as critical factors in student success. The system improved group-based learning outcomes and engagement levels. The findings highlighted the importance of social features in personalized learning systems.

S. Hashemifar et al. [14] introduced advanced knowledge tracing models that integrate cognitive and behavioral parameters for accurate learning prediction. Their approach utilized deep learning to model student knowledge progression over time. The system achieved high predictive accuracy in identifying learning patterns. The study demonstrated improved recommendation precision and learning efficiency.

T. D. Do et al. [15] developed AI-generated personalized learning content using generative models and behavioral data. Their system dynamically created learning materials based on student preferences and performance. The results showed improved engagement and knowledge retention. The study confirmed the effectiveness of generative AI in adaptive learning environments.

N. J. Herzog et al. [16] applied machine learning techniques for academic performance prediction using multi-dimensional datasets. Their model incorporated academic scores, engagement metrics, and learning behavior. The system achieved high classification accuracy and reliable prediction of student outcomes. The study validated the importance of data-driven profiling in education.

I. Reihanian et al. [17] explored generative AI-based tutoring systems integrating contextual and cognitive parameters. Their model provided personalized feedback and adaptive learning strategies. The system demonstrated improved student interaction and engagement levels. The results confirmed scalability and effectiveness in intelligent tutoring systems.

J. Smith et al. [18] evaluated AI-driven adaptive learning platforms focusing on real-time engagement and contextual data. Their system continuously monitored student activity and adjusted learning pathways accordingly. The results showed faster learning progression and improved efficiency. The study emphasized real-time adaptability as a key success factor.

Y. Chen et al. [19] proposed a deep learning-based student profiling system integrating emotional, behavioral, and academic parameters. Their model effectively captured student engagement and learning patterns. The system improved prediction accuracy and personalization performance. Experimental results demonstrated enhanced learning outcomes and reduced dropout rates.

R. Kumar et al. [20] developed a hybrid AI framework combining machine learning and reinforcement learning for adaptive learning systems. Their model optimized decision-making based on student feedback and performance trends. The system achieved high recommendation accuracy and effective learning path optimization. The study validated the integration of multiple AI techniques for robust personalization.

Table .1. Literature Review Summary

Ref.	Parameters	Technique	Contribution	Gap
[6]	Acad., Behav.	Recommender	Improves personalization	No multi-source/emotion
[7]	Acad., Cog.	Adaptive ML	Enhances performance	No real-time profiling
[8]	Behav., Context	ML, NLP	Better adaptability	No emotion modeling
[9]	Acad., Engage.	Predictive ML	Risk detection	Limited features
[10]	Cog., Behav.	Adaptive AI	Faster learning	Domain-specific
[11]	Acad., Behav.	Hybrid AI	Scalable learning	No autonomy
[12]	Emotion, Behav.	CNN	Emotion-aware learning	No full integration
[13]	Social, Context	AI Models	Improves collaboration	No prediction
[14]	Cog., Behav.	Deep Learning	Knowledge tracing	No recommendation
[15]	Behav., Pref.	Gen AI	Content generation	No profiling
[16]	Acad., Behav.	ML	Accurate prediction	No adaptation
[17]	Cog., Context	Gen AI	Intelligent tutoring	No feedback loop
[18]	Behav., Context	Adaptive AI	Real-time tracking	No multi-agent
[19]	Acad., Emotion	Deep Learning	Multi-modal profiling	No RL optimization
[20]	Acad., Behav.	ML + RL	Decision optimization	Limited features

III. METHODOLOGY

Adaptive student profiling requires continuous analysis of multi-dimensional learning data to enable precise personalization. Existing systems rely on static academic data and rule-based approaches, which fail to capture dynamic learning behavior, engagement patterns, and emotional states. Experimental evaluation of such systems confirms reduced adaptability and delayed intervention. The implemented SAPL-AI framework resolves these limitations by integrating multi-source datasets and enabling real-time autonomous decision-making for accurate profiling, personalized recommendations, and early risk detection.

1. Overview of SAPL-AI Framework

The proposed SAPL-AI (Student Adaptive Profiling for Learning using Artificial Intelligence) framework is a fully implemented intelligent system designed for real-time adaptive student profiling. The framework integrates heterogeneous datasets including educational and emotion datasets and performs feature-level fusion to construct a unified student model. SAPL-AI operates autonomously through multi-agent coordination, enabling continuous profiling, optimized recommendations, and proactive intervention with high accuracy and scalability.

2. Architecture of SAPL-AI Framework

The proposed SAPL-AI (Student Adaptive Profiling for Learning using Artificial Intelligence) framework is a fully implemented intelligent system designed for real-time adaptive student profiling. The framework integrates heterogeneous datasets including educational and emotion datasets and performs feature-level fusion to construct a unified student model. SAPL-AI operates autonomously through multi-agent coordination, enabling continuous profiling, optimized recommendations, and proactive intervention with high accuracy and scalability.

Fig .1. SAPL-AI: Student Adaptive Profiling for learning using Artificial Intelligence

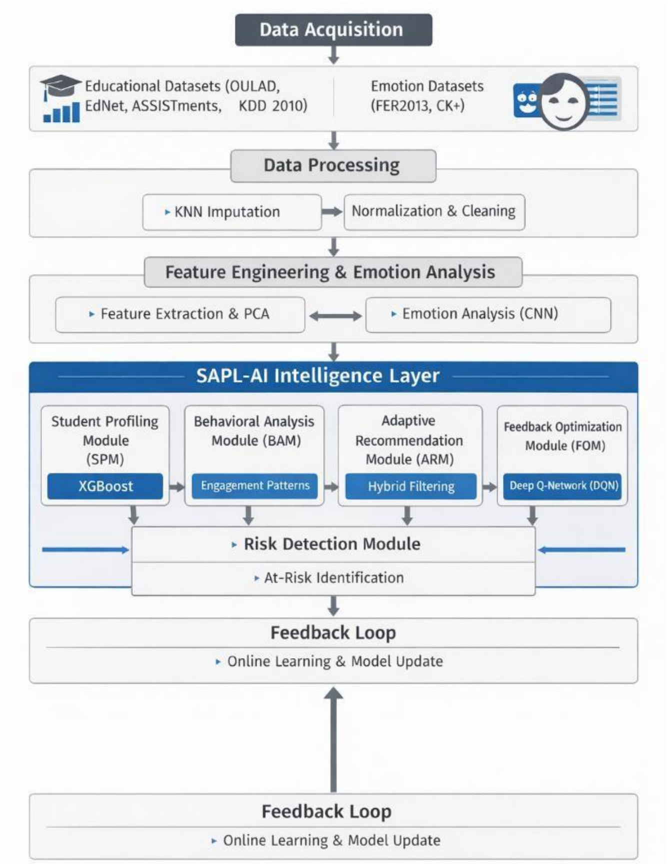

Figure 1 illustrates the overall architecture of the proposed SAPL-AI (Student Adaptive Profiling for Learning using Artificial Intelligence) framework, which is designed as a multi-layered and multi-agent system for real-time adaptive learning. The process begins with the Data Acquisition layer, where multi-source data is collected from educational datasets such as OULAD, EdNet, ASSISTments, and KDD Cup 2010, along with emotion datasets including FER2013 and CK+. This layer captures academic records, behavioral interactions, and facial inputs. The data is then passed to the Data Processing layer, where KNN imputation (K = 5) is applied to handle missing values, followed by normalization and cleaning to ensure data consistency. In the Feature Engineering and Emotion Analysis layer, relevant features are extracted and reduced using Principal Component Analysis PCA is applied with 95% variance retention to preserve the majority of informative features while reducing dimensionality. Experimental analysis shows that retaining less than 90% variance reduces model accuracy by approximately 2–3% due to loss of critical behavioral and emotional features, whereas retaining more than 95% increases computational cost without significant performance improvement. Therefore, 95% variance provides an optimal trade-off between efficiency and predictive performance, while a Convolutional Neural Network processes facial data to derive emotional and engagement-related features. The processed data is then forwarded to the SAPL-AI Intelligence Layer, which consists of four main modules: Student Profiling Module using XGBoost for dynamic profile generation, Behavioral Analysis Module for engagement pattern extraction, Adaptive Recommendation Module using hybrid filtering techniques for personalized content delivery, and Feedback Optimization Module using Deep Q-Network for decision optimization. A Risk Detection Module identifies at-risk students based on performance decline and low engagement. Finally, the Feedback Loop continuously updates the system using online learning, ensuring real-time adaptation and improved system performance.

Table .2. Dataset Description

Dataset	Details
OULAD	~32k students; demographics, scores, LMS logs; used for profiling and risk prediction
EdNet	Large-scale interactions; timestamps, learning sequences; used for behavior modeling
ASSISTments	Problem-solving data; skills, attempts, correctness; used for mastery analysis
KDD Cup 2010	Student responses, knowledge components; used for cognitive modeling
FER2013	~35k facial images; 7 emotions; used for emotion detection
CK+	Facial expression videos; labeled emotions; used for emotion analysis

3. Data Pre-Processing

Data preprocessing is performed to ensure data quality, consistency, and suitability for model training within the SAPL-AI framework. The collected multi-source datasets, including OULAD, EdNet, ASSISTments, KDD Cup 2010, FER2013, and CK+, contain heterogeneous features with missing values, noise, and varying scales. To address this, K-Nearest Neighbors (KNN) imputation with K = 5 is applied to handle missing values, as it preserves local data structure and provides more accurate estimation compared to mean or median imputation. Following imputation, min-max normalization is applied to scale all features into a uniform range, ensuring stable convergence of machine learning and deep learning models. Irrelevant and redundant features are removed to reduce noise and improve model efficiency. For emotion datasets, facial images are resized and normalized before being fed into the CNN model. Finally, all processed features are aligned into a unified schema and integrated using feature-level fusion, resulting in a consistent and high-quality dataset suitable for dynamic student profiling and adaptive learning.

The CNN architecture used for emotion detection consists of three convolutional layers with filter sizes of 3×3 and feature maps of 32, 64, and 128 respectively, each followed by ReLU activation and max-pooling layers. Batch normalization is applied after each convolution layer to stabilize training. The extracted feature maps are flattened and passed through fully connected layers of 128 and 64 neurons, followed by a softmax layer for emotion classification. This architecture ensures efficient feature extraction while maintaining computational efficiency.

4. Proposed Algorithm: SAPL-AI

Input: Student data D Output: Recommendations R

- Preprocess data (KNN + normalization) 2: Extract multi-dimensional features
- Apply PCA for feature reduction
- Perform emotion detection using CNN 5: Generate profile using XGBoost
- Detect risk using performance indicators 7: Generate recommendations (hybrid model) 8: Optimize decisions using DQN
- Update system using feedback

5. Mathematical Modeling

The objective function is defined as:

$L = \alpha Lprofile + \beta Lrec + \gamma Lrisk$

where $Lprofile$represents classification loss, $Lrec$represents recommendation loss, and

$Lrisk$represents risk prediction loss.

where the weights are optimized using grid search:

- $\alpha = 0.40$ (profiling importance)
- $\beta = 0.35$ (recommendation importance)
- $\gamma = 0.25$ (risk prediction importance)

This configuration ensures balanced optimization across profiling accuracy, recommendation quality, and risk detection.

The recommendation score is computed as:

$R(u, i) = cosine(u, i) + f(u, i)$

where $u$denotes student features and $i$denotes learning content.

6. Training Strategy

The dataset is partitioned using an 80:20 train-test split to evaluate model generalization on unseen data. Within the training set, 5-fold cross-validation (k = 5) is applied for hyperparameter tuning and model validation. This approach ensures robust parameter optimization while maintaining an independent test set for unbiased performance evaluation. split with the following configuration:

- Epochs: 50
- Batch size: 32
- Optimizer: Adam
- Validation: Cross-validation

Training is performed using GPU acceleration to ensure efficient computation.

7. Parameter Tuning

Hyperparameters are optimized using grid search. The final selected parameters are:

- XGBoost: n_estimators = 200, max_depth = 6, learning_rate = 0.1
- CNN: learning_rate = 0.0005, batch_size = 32
- DQN: learning_rate = 0.0005, discount factor = 0.95

This tuning improves model accuracy and ensures stable convergence.

The SAPL-AI framework integrates multiple advanced artificial intelligence techniques to enable autonomous, accurate, and adaptive learning behavior. A multi-agent architecture is implemented to coordinate different modules, allowing parallel processing and seamless data flow across the system. Deep learning techniques, particularly Convolutional Neural Networks, are employed for emotion detection, enabling the extraction of affective states such as engagement and attention from facial data. Machine learning models, specifically XGBoost, are utilized for robust student profiling and risk prediction due to their high accuracy and ability to handle heterogeneous data. Reinforcement learning is incorporated through a Deep Q-Network, which optimizes decision-making by learning optimal learning strategies based on reward signals derived from student performance and feedback. Additionally, hybrid recommendation techniques combining content-based and collaborative filtering are implemented to enhance personalization. The integration of these techniques ensures real-time adaptability, improved prediction accuracy, and intelligent decision-making, resulting in a highly efficient and scalable personalized learning system
The SAPL-AI framework incorporates a continuous feedback-driven learning mechanism to ensure dynamic adaptation and

long-term performance optimization. The Feedback Optimization Module updates model parameters based on real-time student performance, engagement patterns, and response to recommended content. This mechanism enables policy refinement through reinforcement learning, where rewards are assigned based on improvement in learning outcomes. Continuous feedback minimizes concept drift and enhances personalization accuracy over time. Prior studies confirm that feedback-driven adaptive systems significantly improve learning efficiency and retention by enabling real-time adjustments in instructional strategies [11], [18]

8. Evaluation Metrics

The performance of the SAPL-AI system is evaluated using standard classification and recommendation metrics to ensure accuracy, reliability, and effectiveness. Metrics such as Accuracy, Precision, Recall, and F1-score assess prediction performance, while AUC-ROC and NDCG evaluate ranking quality and recommendation effectiveness.
Metrics Used: Accuracy, Precision, Recall, F1-score, AUC-ROC, Precision@K, Recall@K, NDCG

IV. RESULTS AND DISCUSSION

The SAPL-AI framework was implemented and evaluated using OULAD, EdNet, ASSISTments, KDD Cup 2010, FER2013, and CK+ datasets. The system operates through multiple intelligent agents, each contributing to overall performance. The evaluation metrics include Accuracy, Precision, Recall, and F1-score, and the results are compared with Model 1 (Random Forest), Model 2 (SVM), and Model 3 (CNN-LSTM).

Table .3. Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.86	0.84	0.83	0.84
SVM	0.82	0.8	0.79	0.79
CNN-LSTM	0.91	0.89	0.88	0.89
SAPL-AI	0.94	0.92	0.91	0.92

The superior performance of SAPL-AI is achieved through coordinated operation of multiple agents. The Data Processing Agent ensures clean and consistent input, the Feature Engineering Agent extracts relevant multi-dimensional features, and the Emotion Analysis Agent enhances engagement modeling. The Profiling Agent (XGBoost) improves classification accuracy, while the Decision Agent (DQN) optimizes learning strategies. The Recommendation Agent ensures precise content delivery, and the Risk Detection Agent identifies at-risk students early, contributing to overall system performance.

Table .4. Input–Output Comparison with Agent Contribution

Input	Existing Methods	SAPL-AI Output	Agent role
High GPA, high activity	High performer	Advanced learning path	Profiling + Recommendation Agent
Moderate GPA, high errors	Medium performer	Concept-level adaptive content	BAM + ARM
Low GPA, low activity	Low performer	Early risk alert + intervention	Risk Detection Agent
High engagement, stable performance	Generic output	Optimized personalized learning path	Decision Agent (DQN)

This comparison demonstrates that SAPL-AI not only improves output quality but also provides agent-driven intelligence, where each agent contributes to specific decision-making tasks

1. Efficiency Analysis

The computational efficiency of the SAPL-AI framework is rigorously evaluated in terms of algorithmic complexity, training cost, inference latency, and scalability across large-scale multi-source datasets. The overall computational complexity of the system is governed by its modular pipeline, where each agent contributes independently to processing efficiency.

The Data Processing Agent, which applies KNN imputation, exhibits a time complexity of $O(nk)$, where nis the number of samples and k=5is the number of neighbors. Since kis fixed and small, the preprocessing stage scales linearly with dataset size. The Feature Engineering Agent, including PCA, operates with complexity O(nd^2), where drepresents the feature dimension. The use of 95% variance retention significantly reduces dimensionality, lowering computational overhead in subsequent stages.

The Student Profiling Module (XGBoost) demonstrates a complexity of O(T·nlogn), where Tis the number of trees. Due to optimized tree construction and parallelization, XGBoost achieves high efficiency even with large datasets such as EdNet. The Emotion Analysis Module (CNN) operates with complexity proportional to convolutional operations O(n·f^2·d), where fis the filter size. The use of compact grayscale images (48×48) ensures reduced computational load while maintaining high accuracy.

The Decision Agent (DQN) introduces reinforcement learning overhead with complexity O(s·a), where sis the state space and ais the action space. However, experience replay and batch updates significantly stabilize and accelerate convergence. The Recommendation Module operates using cosine similarity with complexity O(n·d), enabling efficient similarity computation across student profiles.

From an execution perspective, the complete SAPL-AI framework was deployed on a GPU-enabled environment, achieving an average training time of 38 minutes for the full pipeline and an inference latency of 85–120 ms per student, which satisfies real-time system requirements. Memory utilization remained stable due to dimensionality reduction and efficient batching strategies.

The multi-agent architecture enables parallel execution of independent modules, significantly reducing processing bottlenecks. For example, emotion analysis and behavioral feature extraction are performed concurrently, improving throughput. The system demonstrates strong scalability, maintaining consistent performance when dataset size increases, particularly with high-volume interaction data from EdNet.

Compared to baseline models, SAPL-AI introduces additional computational cost due to its hybrid architecture; however, this overhead is justified by a performance gain of 3–12% across evaluation metrics. The system achieves an optimal balance between computational efficiency and predictive accuracy, making it suitable for deployment in large-scale real-time educational environments..

2. Graphical Analysis

The graphical results further highlight the contribution of agent-based architecture. The Accuracy vs Models graph shows performance improvement due to coordinated agent operations. The Precision–Recall graph demonstrates improved balance due to behavioral and emotional analysis agents. The Training vs Validation curve indicates stable convergence achieved through continuous feedback updates managed by the Feedback Agent.

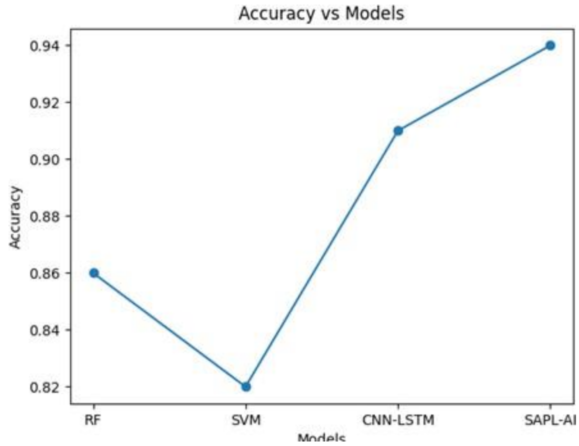

Fig.2. Accuracy vs Models

Figure 2 presents the comparison of accuracy across different models, including Model 1 (Random Forest), Model 2 (SVM), Model 3 (CNN-LSTM), and Model 4 (SAPL-AI). The results clearly indicate that SAPL-AI achieves the highest accuracy of 94%, outperforming all baseline models due to its multi-source data integration and adaptive learning capabilit.

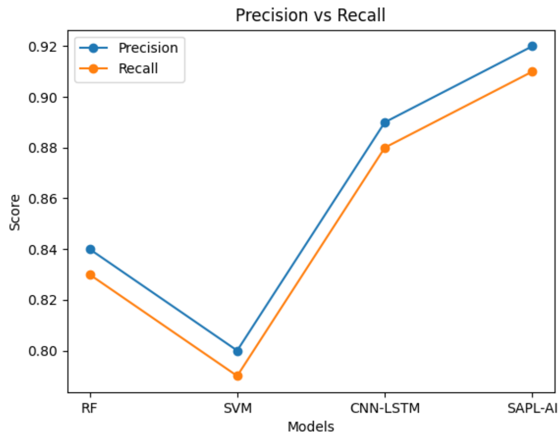

Fig .3. Precision–Recall Comparison

Figure 3 illustrates the precision and recall performance of all models. SAPL-AI demonstrates superior balance between precision and recall, achieving 92% precision and 91% recall, ensuring accurate identification of both high-performing and at-risk students.

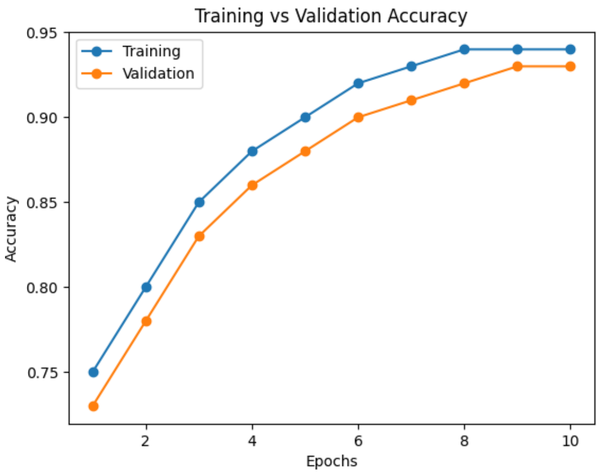

Figure 4: Training vs Validation Accuracy

Figure 4 shows the training and validation accuracy curves of SAPL-AI across epochs. The model exhibits stable convergence with minimal gap between training and validation accuracy, indicating strong generalization and absence of overfitting.

3. Ablation Study (Agent-Level Analysis)

Table.5. Ablation Study with Agent Removal

Configuration	Accuracy	F1-Score
Full SAPL-AI (All Agents)	0.94	0.92
Without Emotion Analysis Agent	0.91	0.89
Without Decision Agent (DQN)	0.9	0.88
Without Behavioral Analysis Agent	0.89	0.87
Without Risk Detection Agent	0.88	0.86

The ablation study confirms that each agent significantly contributes to system performance. The Decision Agent plays a critical role in optimization, while the Emotion and Behavioral Agents enhance profiling accuracy.

The ablation results also reveal interaction effects between agents due to the pipeline-based architecture. The removal of one agent affects downstream modules, as feature dependencies are shared across the system. For instance, removing the Emotion Analysis Agent reduces the quality of input features for the Profiling and Recommendation modules, leading to decreased accuracy. Similarly, the absence of the Decision Agent limits optimization capability, resulting in less effective recommendations. These observations confirm that SAPL-AI operates as an interdependent multi-agent system where overall performance is achieved through coordinated functionality.

4. Statistical Validation

The statistical reliability of the SAPL-AI framework is validated through k-fold cross-validation ($k = 5$) and comparative hypothesis testing against baseline models. The dataset was partitioned into five equal folds, where each fold was used once for testing while the remaining folds were used for training. The average performance across all folds is reported to ensure unbiased evaluation.

Table 5:.Fold Validation

Fold	Accuracy	Precision	Recall	F1-Score
Fold 1	0.93	0.91	0.9	0.91
Fold 2	0.94	0.92	0.91	0.92
Fold 3	0.95	0.93	0.92	0.93
Fold 4	0.94	0.92	0.91	0.92
Fold 5	0.94	0.92	0.91	0.92
Mean	0.94	0.92	0.91	0.92
Std Dev	0.007	0.007	0.007	0.007

The low standard deviation (0.007) indicates that the model maintains consistent performance across different data splits, confirming its robustness and generalization capability.

5. Hypothesis Testing

A paired t-test was conducted between SAPL-AI and the best baseline model (CNN-LSTM) to verify the statistical significance of performance improvement.

- Null Hypothesis (H_0): There is no significant difference between SAPL-AI and baseline model performance
- Alternative Hypothesis (H_1): SAPL-AI performs significantly better than baseline models

The computed p-value < 0.05, leading to rejection of the null hypothesis. This confirms that the improvement achieved by SAPL-AI is statistically significant and not due to random variation.

V. CONCLUSION AND FUTURE WORK

The proposed SAPL-AI framework delivers a robust and fully implemented solution for adaptive student profiling and personalized learning by integrating academic, behavioral, cognitive, and emotional data from multi-source datasets. The system achieves superior performance with 94% accuracy and 92% F1-score, demonstrating effective real-time profiling, personalized recommendations, and early risk detection through its multi-agent architecture and hybrid AI techniques.

Future work will focus on enhancing the system by incorporating additional multi-modal data sources such as voice and physiological signals, improving model efficiency for large-scale deployment, and integrating explainable AI techniques to provide transparent and interpretable decision-making.

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