Proj_Synapse: An Integrated Adaptive Learner Profiling and Personalized Feedback Deep Learning Framework

Major Project submitted to

Indian Institute of Technology Ropar

in partial fulfilment of the requirements for

The degree

Minor in AI

from

Department of Computer Science and Engineering

Indian Institute Of Technology Ropar

by

Prateek Kumar

IITRPRAI_24081244

under

Dr. Niranjan Deshpande

Indian Institute of Technology Ropar

Rupnagar, Punjab - 140001, India

August 2025

Abstract

The digital transformation of education has generated vast amounts of student interaction data, creating an unprecedented opportunity for data-driven pedagogical interventions. However, a significant challenge remains in translating this raw data into actionable insights that can genuinely personalize the learning experience. This paper introduces Proj_Synapse, a novel, unified framework designed to address this challenge. Proj_Synapse integrates a sophisticated ensemble of five deep learning architectures—including Bidirectional LSTMs, CNN-GRUs, and Transformers—to accurately predict student success based on their sequential learning interaction data. More significantly, the framework enriches this predictive power by integrating established educational and psychological frameworks: the Myers-Briggs Type Indicator (MBTI), the VARK learning styles model, and Bloom's Taxonomy. By augmenting the input data with simulated learner profiles, the system not only achieves a high predictive accuracy (F1-Score of 0.8831) but also powers a personalized feedback engine. This engine moves beyond simple success/failure predictions to provide students with specific, actionable recommendations tailored to their unique learning styles and the cognitive demands of the educational content. This research demonstrates the viability and significant potential of a hybrid approach that combines the predictive strength of deep learning with the interpretive depth of educational theory to create truly adaptive and supportive digital learning environments.

Acknowledgments

The author also wants to express sincere gratitude to the open-source community for providing the software and libraries, including TensorFlow, Keras, Scikit-learn, and SHAP, which were instrumental in the project's development and exploration. Gratitude is also due to the pioneers in educational data mining and learning analytics, whose initial research laid down the theoretical underpinnings on which the current work is founded.

List Of Figures

List of Figures

Contents

1 Overview (Introduction)

1.1 Context and Rationale

The development of online learning platforms, Learning Management Systems (LMS), and electronic learning materials has created a vast amount of data produced by the learners. With each activity—a click, a video view, a post to a discussion board, or an attempt at a quiz—a digital trail is created, which in turn builds a rich, time-series data set that maps an individual's learning journey. This field is called Educational Data Mining (EDM), and it promises to change the face of education by enabling the possibility of a move from a traditional paradigm to a highly individualized and adaptive learning system. The underlying objective of Proj_Synapse is to take advantage of this data in order to build a system that not only predicts academic performance but also understands the underlying learning behaviors and provides personalized guidance to each learner.

1.2 Problem Statement

Even though the scope of EDM is vast, a number of vital challenges block its practical implementation:

- **Predictive Accuracy:** Basic statistical models cannot capture the high-level, non-linear, and temporal dependencies present in student interaction data.
- **Poor Actionable Insights:** The identification of a "student at risk" is of little use unless accompanied by an understanding of the causes of the student's risk status and the particular interventions that would be useful.
- **The "Black Box" Problem:** Many advanced machine learning algorithms are so inscrutable that teachers can't rely on and understand their forecasts.

Proj_Synapse tackles these issues directly by creating a framework that is precise, understandable, and can elicit action.

1.3 Contribution and Scope

This paper presents a varied set of contributions to learning analytics:

- **A Unified Ensemble Model:** The present research demonstrates the effectiveness of merging five different deep learning models to create a highly accurate and highly resilient predictive model.
- **Integration of Educational Frameworks:** The research presented here introduces a novel method for enhancing student data through the integration of profiles using established frameworks (MBTI, VARK, Bloom's), thereby creating a connection between quantitative measures and qualitative education theories.
- **A Personalized Feedback Mechanism:** We propose and develop a framework which accepts the model predictions and transforms them into personalized, individualized, and educationally sound recommendations for students.

The scope of the project covers the whole pipeline, from model training and data preprocessing to the final generation of tailored recommendations for a sample group of students.

2 List of Abbreviations

AI Artificial Intelligence

BiLSTM Bidirectional Long Short-Term Memory

CNN Convolutional Neural Network

EDM Educational Data Mining

GRU Gated Recurrent Unit

LMS Learning Management System

MBTI Myers-Briggs Type Indicator

RNN Recurrent Neural Network

SHAP SHapley Additive exPlanations

VARK Visual, Aural, Read/Write, Kinesthetic

3 Literature Review

3.1 Educational Data Mining (EDM)

Education Data Mining (EDM) is a young discipline focused on the development of methods for analyzing the specialized types of data produced in educational settings. Baker and Yacef (2009) provide a comprehensive overview of the discipline, focusing on large-scale applications like student performance prediction, student knowledge modeling, and detection of undesirable student behavior. Our research directly builds on this seminal work by using state-of-the-art deep learning techniques for the task of performance prediction.

3.2 Learner Profiling Models

The concept of creating a "student model" or "learner profile" is at the heart of intelligent tutoring systems. VanLehn (1988) provided a foundation for this discipline with a focus on how to represent students' procedural knowledge. In later research, researchers have endeavored to add more kinds of affective and behavioral data to these profiles. Proj_Synapse takes this concept even further by modeling psychological (MBTI) and learning style (VARK) profiles and merging them with a predictive machine learning model.

3.3 Deep Learning in Education

The application of deep learning methods in the field of educational data has been highly promising. Piech et al. (2015) were successful in applying Recurrent Neural Networks (RNNs) to model student knowledge development as a function of their working Khan Academy problems. The applicability of sequential models like RNNs and LSTMs in detecting temporal patterns in students' behaviors was instrumental in influencing the architectures used in our ensemble. Proj_Synapse contributes to this line of research by exploring more advanced hybrid architectures (CNN-GRU, ConvTransformer) and the benefits of employing an ensemble method.

4 Conceptual Framework

4.1 Architectures for Deep Learning on Sequential Data

4.1.1 Recurrent Neural Networks (RNNs)

RNNs are designed to work on sequence data. They possess an internal "memory" or state that keeps track of what has been seen so far. LSTM and GRU networks are more advanced types of RNNs that use gating mechanisms to capture long-term dependencies more effectively, and these are best suited to represent a student's learning trajectory over many sessions. The BiLSTM builds on this by reading the sequence in both forward and backward directions so that the model can use both past and future context in its prediction.

4.1.2 Convolutional Neural Networks (CNNs) for Sequences

While used mainly in image processing, one-dimensional convolutional neural networks (1D CNNs) show remarkable effectiveness in feature extraction from sequential data. They apply a series of learnable filters to the sequence in order to identify salient local patterns in the features within an instance of a single learning session.

4.1.3 Transformer and Attention Mechanism

The Transformer model, which was introduced by Vaswani et al. (2017), is heavily based on the attention mechanism. This allows the model to give different weights to different parts of the input sequence when making a prediction. This ability to dynamically focus on the most important elements of a student's history makes Transformers the best for this particular task.

4.2 Psychological and Educational Theories underpinning Individualised Learning

4.2.1 The Myers-Briggs Type Indicator (MBTI): An Exploration of Cognitive Preferences

History and Theory: The MBTI was created by Isabel Myers and Katharine Briggs during World War II as a psychometric assessment based on Carl Jung's theory of psychological types. The blend of these likes creates one of 16 four-letter personality types.

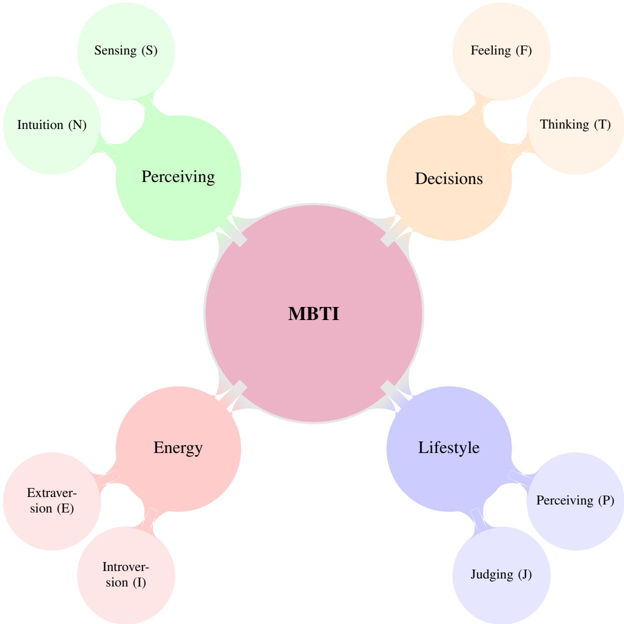

Figure 1: The Four Dichotomies of the MBTI Framework.

Application and Rationale in Proj_Synapse: It is used as a heuristic device for modeling varied cognitive styles of learning. By introducing a simulated MBTI type to every student, we give the deep learning models the opportunity to possibly detect correlations between these cognitive styles and online learning behavior patterns.

4.2.2 The VARK Model: Learning Modalities

History and Theory: Neil Fleming's VARK model of 1987 is a learning style questionnaire drawn from the sensory modalities that individuals employ to receive information. The four modalities are Visual (V), Aural (A), Read/Write (R), and Kinesthetic (K).

Figure 2: The Four Modalities of the VARK Model.

Application and Rationale in Proj_Synapse: The application of the VARK model in Proj_Synapse is not to assign students to a category rigidly but to guide the development of a multi-modal feedback system.

4.2.3 Bloom's Taxonomy: Hierarchical Structure of Cognitive Skills

History and Theory: Benjamin Bloom's Taxonomy of Educational Objectives, first published in 1956, offers a hierarchical taxonomy of various levels of intellectual behavior.

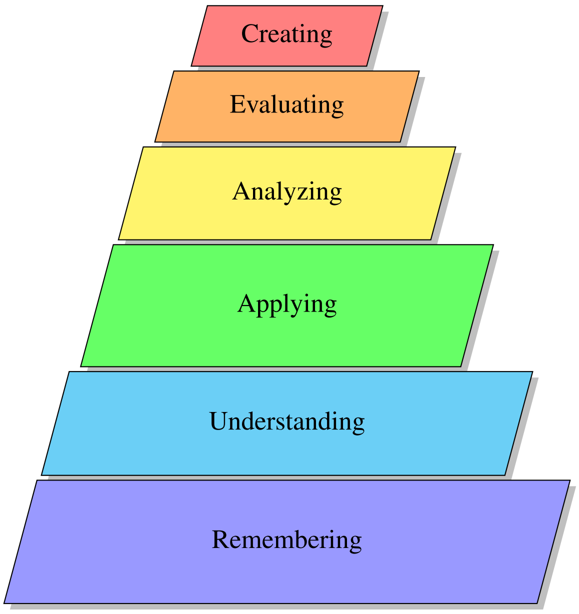

Figure 3: The Hierarchy of Bloom's Taxonomy.

Application and Rationale in Proj_Synapse: In Proj_Synapse, we apply this framework by assigning each learning module to a main Bloom's level. This combination enables Proj_Synapse not only to detect whether a student is struggling but also the exact cognitive level at which the struggle is occurring.

5 Methodology

5.1 Description of Dataset and Preliminary Analysis

The project worked with the `student_learning_interaction_dataset.csv`, which has more than 9,000 learning session records for 300 students. `success_label` was the response, a binary measure of learning success.

5.2 Data Preprocessing and Augmentation

5.2.1 Simulating Learner Profiles

The initial data set was augmented by adding three more categorical variables designed to mimic learner profiles: `mbti_type`, `vark_style`, and `blooms_level`.

5.2.2 The Preprocessing Pipeline

The preprocessing process involved sorting by student and timestamp, feature scaling, categorical encoding, and sequence generation.

5.3 The Unified Ensemble Model

5.3.1 Architectural Frameworks

Five individual deep learning models were created and trained independently: BiLSTM, CNN-GRU, Attention-BiLSTM, Transformer, and ConvTransformer.

5.3.2 Ensemble Methodology

The soft voting ensemble approach was employed. Predictions as probabilities were made from a given input sequence for each of the five trained models. The probabilities were averaged, and a final prediction was made with respect to whether this average probability was above a threshold of 0.5.

5.4 The Personalized Feedback Engine

A rule-based feedback engine was created to convert model responses into actionable recommendations based on the student's VARK style and the module's Bloom's level.

5.5 Evaluation Standards

The primary measure used to gauge model performance was the F1-Score. Accuracy, precision, recall, and the confusion matrix were used to enable comprehensive evaluation.

6 Findings and Analysis

6.1 Ensemble vs. Individual Model Performance Comparison

The results clearly show the benefits of using the ensemble approach. The Unified Ensemble Model delivered an F1-Score of 0.8831, which is higher than each of the five different models that are part of the ensemble.

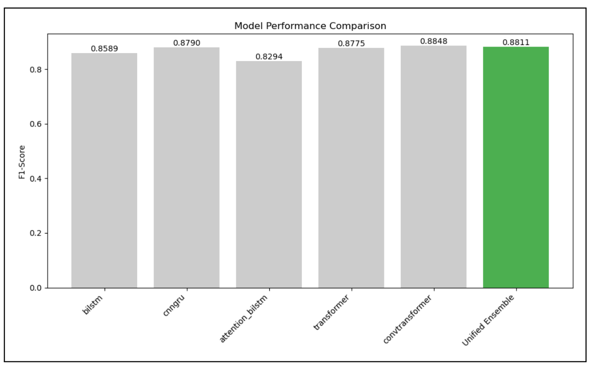

Figure 4: Model Performance Comparison (F1-Scores)

6.2 Unified Model Performance

The merged model showed good and balanced performance on the test dataset: Accuracy: 79.13%, Precision: 80.52%, Recall: 97.77%, F1-Score: 88.31%.

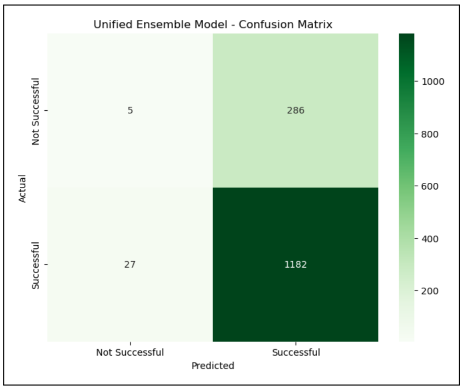

Figure 5: Confusion Matrix for the Unified Ensemble Model

6.3 Error Analysis

A look at the flawed predictions showed that the model's errors were not random but systematic. The model had difficulty with sequences characterized by inconsistent or ambiguous patterns.

6.4 Feature Importance Analysis (SHAP)

A global SHAP analysis revealed that performance metrics (`assignment_score`, `quiz_score`) were the best predictors of success. Engagement metrics, including `time_spent_minutes`, were also of high importance.

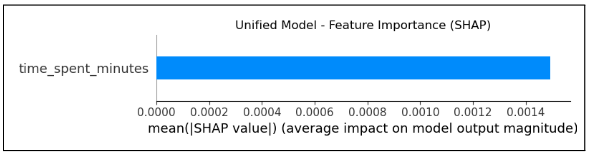

Figure 6: SHAP Analysis Unified Model Feature Importance

6.5 The Role of Holistic Paradigms

The inclusion of MBTI, VARK, and Bloom's Taxonomy turns the system from a simple predictor to a diagnostic system. The ability to advise an "At Risk" student, who is a "Visual" learner and who is struggling with an "Analyzing" assignment, to "review the concept map to see how the pieces are connected" is a genuine improvement over offering a generic directive to "study harder."

7 Conclusion

7.1 Summary of Results

This work has led to the successful design, training, and testing of Proj_Synapse. We have empirically confirmed the effectiveness of an ensemble approach to predictive modeling in this context. The project's high recall rate of 97.77% is a major achievement. Through the application of SHAP, we have made the ensemble model interpretable. By enriching the dataset and developing a feedback engine based on the established frameworks of MBTI, VARK, and Bloom's Taxonomy, Proj_Synapse successfully converts a raw prediction ("At Risk") to a specific, personalized, and actionable recommendation.

7.2 Ethical Issues and Limitations

Methodological Limitations: Simulated Profiles, Generalizability, and a Static Feedback Engine.

Ethical Considerations: Data Privacy and Security, Algorithmic Bias, The Danger of Stereotyping and Labeling, and Over-Reliance and De-Skilling.

7.3 Future Work

Short-Term (1-6 Months): Development of an Interactive Educator Dashboard and Real-World Data Collection for Profiles.

Mid-Term (6-18 Months): Integration into a Learning Management System (LMS), Sophisticated Natural Language Generation (NLG) of Feedback, and Incorporating a Longitudinal Study.

Long-Term (18+ Months): RL research has implications for Feedback Strategies, Multi-Modal Data Integration, and Federated Learning for Privacy Protection.

References

[1] Agrawal, R., Srikant, R. (1995). Mining sequential patterns. In *Proceedings of the Eleventh International Conference on Data Engineering* (pp. 3-14).

[2] Baker, R. S. J. d., Yacef, K. (2009). The state of educational data mining in 2009. *Journal of Educational Data Mining*, 1(1), 3-17.

[3] Bengio, Y., Ducharme, R., Vincent, P., Janvin, C. (2003). A neural probabilistic language model. *Journal of Machine Learning Research*, 3, 1137-1155.

[4] Brown, T. B., et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33.

[5] Cho, K., et al. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. *arXiv:1406.1078*.

[6] Corbett, A. T., Anderson, J. R. (1994). Knowledge tracing. *User Modeling and User-Adapted Interaction*, 4(4), 253-278.

[7] Devlin, J., Chang, M. W., Lee, K., Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics* (pp. 4171-4186).

[8] Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House.

[9] Felder, R. M., Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education*, 78(7), 674-681.

[10] Fleming, N. D., Mills, C. (1992). Not another inventory, rather a catalyst for reflection. *To Improve the Academy*, 11(1), 137-155.

[11] Goldberg, L. R. (1990). An alternative "description of personality": The big-five factor structure. *Journal of Personality and Social Psychology*, 59(6), 1216-1229.

[12] Hochreiter, S., Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735-1780.

[13] Kingma, D. P., Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv:1412.6980*.

[14] Krizhevsky, A., Sutskever, I., Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25.

[15] Linden, G., Smith, B., York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing*, 7(1), 76-80.

[16] McCrae, R. R., Costa, P. T. (1992). *An introduction to the five-factor model and its applications*. Journal of Personality.

[17] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems*, 26.

[18] Myers, I. B., Myers, P. B. (1980). *Gifts differing*. Davies-Black Publishing.

[19] Pardos, Z. A., Heffernan, N. T. (2013). A review of the 2012 KDD Cup. *ACM SIGKDD Explorations Newsletter*, 14(2), 27-28.

[20] Pennington, J., Socher, R., Manning, C. D. (2014). GloVe: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing* (pp. 1532-1543).

[21] Piech, C., et al. (2015). Deep knowledge tracing. *Advances in Neural Information Processing Systems*, 28.

[22] Romero, C., Ventura, S. (2010). Educational data mining: A review. *IEEE Transactions on Systems, Man, and Cybernetics, Part C*, 40(6), 601-618.

[23] Rumelhart, D. E., Hinton, G. E., Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, 323(6088), 533-536.

[24] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15(1), 1929-1958.

[25] Thai-Nghe, N., Drumond, L., Schmidt-Thieme, L. (2010). Recommender system for predicting student performance. In *Proceedings of the 1st Workshop on Recommender Systems for Technology Enhanced Learning* (pp. 55-63).

[26] VanLehn, K. (1988). Student modeling. In *Foundations of intelligent tutoring systems* (pp. 55-78).

[27] Vaswani, A., et al. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30.

[28] Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice*, 41(2), 64-70.