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RESEARCH ON THE APPLICATION OF DEEP LEARNING MODELS FOR PREDICTING LEARNERS' ACADEMIC PERFORMANCE

SUMMARY OF DISSERTATION ON INFORMATION SYSTEMS

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INTRODUCTION

1. Motivation of the dissertation

he rapid development of data science and artificial intelligence (AI) in education has created new opportunities to improve teaching and learning effectiveness in the context of digital transformation. A prominent application is predicting students' academic performance based on data collected during the learning process, which helps identify early risks of failure and implement timely interventions. This approach directly supports the goals of modern education, including personalized learning experiences and improved graduation rates.

However, many current studies still rely on traditional machine learning models such as linear regression, logistic regression, SVM, decision trees, KNN, and Naive Bayes. While these models are simple, interpretable, and easy to implement, they often fall short in capturing the nonlinear and time-dependent relationships commonly found in educational data. Learning data is typically sequential, reflecting a student's academic progress over time, yet most traditional models only use static features like final grades.

In addition, students' academic performance is influenced by various multidimensional factors, including personal characteristics (such as gender, study habits, part-time jobs, and ability to afford tuition fees), family background (parents' educational level), as well as entry-level academic results such as high school graduation scores, scores from subject combinations used in university admissions (e.g., Math – Chemistry – Biology; Literature – History – Geography), and English proficiency scores. Moreover, admission methods (e.g., transcript-based admission, national exam scores, or priority-based admission) are also important factors that affect students' suitability for and adaptability to the university environment. Contextual factors, such as campus facilities, scholarship policies, teaching quality, and the level of institutional support, also contribute to shaping academic outcomes. The complex and nonlinear relationships among these factors make it difficult for traditional models to fully capture their interactions, thereby requiring the adoption of more advanced analytical methods, such as machine learning and deep learning for more accurate prediction.

Deep learning has emerged as a promising solution due to its ability to automatically learn rich data representations and detect complex patterns without manual feature engineering. Architectures such as LSTM and Transformers are particularly suited to handling sequential data, making them ideal for analyzing learning behavior over time.

However, a major challenge is that deep learning models usually require large amounts of training data, while educational data tends to be small-scale, fragmented, and inconsistently collected across systems.

A promising approach is the use of pre-trained models or transfer learning techniques, which have demonstrated outstanding performance in fields such as computer vision and natural language processing. However, in the context of educational research, a major barrier remains the lack of standardized datasets and domain-specific pre-trained models. To date, the research community has not yet established a shared database or reusable pre-trained model system tailored to academic problems in the field of education.

To address these challenges, this study adopts deep learning as a foundation, while incorporating techniques such as data augmentation, feature selection, and hyperparameter optimization. Additionally, developing hybrid models, combining deep learning with traditional machine learning or integrating multiple deep architectures, offers a promising direction by leveraging the strengths of both: powerful data representation and better interpretability.

The goal of this research is to develop models capable of processing sequential learning data, integrating personal, academic, and social factors, and maintaining predictive effectiveness under data constraints. This contributes to the advancement of Learning Analytics, supports decision-making in higher education, and promotes the application of AI in educational research.

2. Research objectives

General Objective: To research and develop machine learning and deep learning models for analyzing educational data with the goal of early prediction of student academic outcomes.

Specific Objectives:

(1) To propose and compare the performance of modern machine learning and deep learning models: k-Nearest Neighbors (KNN), Decision Trees (DT), Support Vector Machines (SVM), Logistic Regression (LR), Random Forests (RF),Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Transformers,…for predicting academic performance (e.g., semester GPA, graduation classification), with an emphasis on improving accuracy and generalizability.

(2) To construct hybrid deep learning models, perform appropriate feature selection, and apply data augmentation techniques to address the challenges of small-scale and heterogeneous educational datasets.

The experimental evaluation will be conducted using training datasets collected from both domestic and international universities and colleges.

3. Research subjects and scope

Research Subjects: Early prediction problems related to student academic performance can be categorized into several specific types, depending on the objectives and scope of the analysis. Specifically:

- Grade prediction problems: including the prediction of semester Grade Point Average (GPA), annual GPA, cumulative GPA, individual course scores, short-term course results, continuous assessment scores, etc.
- Classification prediction problems: including the prediction of academic classifications for individual courses, semesters, stages of study, or final graduation classifications.

These prediction tasks play an important role in academic early warning systems, helping institutions identify students at risk of failing courses, repeating semesters, or being unable to graduate on time. They also support the recommendation of interventions to improve student performance and provide data-driven evidence for educational administrators to make informed decisions.

In the context of this dissertation, we focus on two core prediction problems:

- The early prediction of semester GPA,
- The early prediction of final graduation classification.

Hereinafter, the term "academic performance" as used in this dissertation refers specifically to "semester GPA" or "graduation classification".

Research Scope: Modern machine learning and deep learning models, including hybrid model architectures.

Datasets collected from Hanoi Metropolitan University (HNMU), Vietnam National University (VNU), and selected publicly available international datasets for reference and benchmarking.

The data used in this research includes:

- Student grade records, collected from university academic management systems.

- Survey data on factors related to students, such as personal information, preferences, academic background prior to university, family circumstances, and socio-occupational factors that may influence academic performance, etc.
- Institutional data from higher education institutions, including facilities, curriculum, and faculty-related information, etc.

4. Research methodology

The research adopts a combination of theoretical study, literature review, empirical research, and survey-based investigation.

5. Key contributions of the dissertation

(1) Two novel methods, NeutroDL and NeutroGNT models, are proposed, integrating the neutrosophic process into deep learning models to enhance early GPA prediction performance.

(2) Two novel hybrid models are proposed: LATCGAd, and AWG-GC for the prediction of graduation classification for students.

(3) Development of 03 multi-attribute datasets from diverse sources and proposal of analytical frameworks tailored to educational data.

From an information systems perspective, where an integrated architecture of data, software, hardware, people, and processes works together to collect, process, and provide information for decision-making, the dissertation makes the following contributions: (i) developing and standardizing educational datasets to support Educational Data Mining (EDM) and Learning Analytics (LA); (ii) designing a rigorous data processing pipeline to ensure data quality and model reliability; (iii) applying advanced deep learning frameworks to develop and optimize predictive models; (iv) leveraging CPU and GPU infrastructures for data processing and real-time analysis; (v) positioning students at the center while providing data-driven insights to support instructors and administrators in improving teaching quality and policy-making; and (vi) integrating IS components to build an intelligent, adaptive educational analytics system, moving toward a data-driven model of higher education management.

6. Layout of the dissertation

This dissertation is presented with a structure that includes an introduction, three main chapters, a conclusion and future development, a list of publications, and references, as follows:

The **Introduction** outlines the scientific significance and urgency of the topic, as well as the reasons for choosing the research topic. It also presents the objectives, subject, scope, methods, key contributions of the dissertation, and contents of the study.

Chapter 1 provides an overview of educational data analysis, highlighting machine learning and deep learning applications in predicting student outcomes. It reviews related research to establish the dissertation's motivation and introduces three key datasets (HNMU1, HNMU2, VNU) from Hanoi Metropolitan University and Vietnam National University, which form the experimental basis for the models developed in later chapters.

Chapter 2 focuses on SGPA prediction using deep learning models combined with Neutrosophy theory to manage data uncertainty. Models such as DNN, CNN, RNN, LSTM, and Transformer are implemented in neutrosophic environments (Neutrosophic DLs) to predict next-semester GPA from historical academic data. To further enhance performance, the chapter introduces NeutroGNT, a hybrid model integrating data neutrosophicization, CGAN-based data generation, noise injection, and Transformer, improving prediction accuracy and adaptability in uncertain conditions.

Chapter 3 shifts to predicting students' graduation classification, a more long-term and system-level task. It introduces LATCGAd and AWG-GC, which leverage graph-based models (Graphformer), advanced GANs (CGAN, WGAN), and Autoencoders, along with AdaLN for stability, to handle small and imbalanced datasets. These models expand data and improve predictive performance, offering higher accuracy, robustness, and scalability for educational analytics systems.

In the **Conclusion and Future development**, the dissertation synthesizes the achieved results and draws several conclusions, while also outlining future research directions based on the findings.

List of publications: The dissertation includes a list of 08 papers authored by the researcher, which have been published or accepted for publication in domestic and international journals and conference proceedings.

Finally, a list of references used in the dissertation is provided.

7. Overview of main content flow

Apart from Chapter 1, which provides an overview and introduces the research problem and datasets, Chapters 2 and 3 form a cohesive structure, presenting two complementary approaches to the early prediction of student academic performance based on both academic and non-academic data. Chapter 2 tackles a regression task to predict semester GPA, a continuous indicator of short-term academic performance. Chapter 3 focuses on a classification task to predict graduation classification, a discrete, long-term outcome. These tasks are closely linked, as multi-semester GPA results serve as key input for the graduation model. Early GPA prediction thus enhances later classification accuracy.

Methodologically, Chapter 2 introduces deep learning models (DNN, LSTM, Transformer) alongside techniques for uncertainty handling (Neutrosophy) and data augmentation (CGAN), laying the groundwork for Chapter 3. Building on this, Chapter 3 develops extended models like LATCGAd and AWG-GC by integrating WGAN, Graphformer, and Autoencoder to handle imbalanced and complex classification data.

The chapters are strongly connected through both data dependencies and a progressive modeling pipeline tailored to the nature of each prediction task.

8. Significance of the dissertation

Academic Significance:

The research contributes to advancing the field of Educational Data Mining (EDM) by integrating deep learning models into educational information systems. The proposed models for predicting GPA and graduation classification, trained on real-world data with high accuracy, provide a strong scientific foundation for applying artificial intelligence in analyzing student learning behaviors.

Practical Applications:

The findings of the dissertation have high applicability in educational management, particularly in:

Personalized learning: supporting academic advising and customized learning pathways for students;

Early identification of at-risk learners: enabling timely interventions by educational institutions;

Data-driven decision-making: assisting in educational planning, evaluation, and policy development.

System-level Contribution:

The dissertation exemplifies the integration of deep learning technologies with core components of educational information systems (data - hardware - software - people - processes), aiming to build a smart, adaptive, and efficient learning environment in the era of artificial intelligence.

The results of this dissertation have been presented at:

1. FS&IS Seminar, School of Information and Communications Technology, Hanoi University of Industry.
2. VNICT Conference, 2024.
3. MCO Conference, 2025.

CHAPTER 1. OVERVIEW OF LEARNING OUTCOME PREDICTION FROM MACHINE LEARNING AND DEEP LEARNING APPROACHES

*This chapter outlines the research context and motivation (Section 1.1), emphasizing the importance of early prediction of student performance. Section 1.2 reviews key machine learning and deep learning foundations. Section 1.3 synthesizes related domestic and international studies, highlighting research gaps. Section 1.4 introduces experimental datasets, including three from Vietnamese universities (**[**CT1**]**, **[**CT3**]**, and **[**CT4**]**) and several international datasets for benchmarking. Finally, Section 1.5 presents the evaluation metrics used to assess and compare model performance in later chapters.*

1.1. Research context and motivation: In the Fourth Industrial Revolution, data drives personalized learning and informed decisions in education. With the growth of educational technologies, academic performance prediction using ML and DL has become central. This dissertation explores DL-based educational data mining to enhance prediction and support strategic management.

Educational Data Mining (EDM) and Learning Analytics (LA) use computational methods to analyze learning data, enabling early intervention, performance prediction, and personalized support. EDM focuses on understanding learning behaviors, while LA tracks and reports learning processes. Together, they drive data-informed educational improvements, despite challenges like data privacy and system integration.

1.2. Machine learning and deep learning methods: ML is categorized into four main types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. KNN, SVM, LR, DT and RF are short introduced in this subsection. DL models like DNNs, CNNs, RNNs, LSTMs and Transformers are designed for complex tasks.

1.3. Overview of related research

Recent international research in EDM and LA highlights the increasing application of ML and DL techniques to predict academic performance and support learning processes. Various ML algorithms have been employed to analyze educational data from LMS and online courses like MOOCs. These methods are effective in predicting student outcomes, including grades, dropout risk, and graduation likelihood. Moreover, DL techniques are gaining traction for their ability to capture complex, non-linear relationships and enhance prediction accuracy. Hybrid models address challenges like imbalanced datasets and incomplete data. Despite promising results, limitations persist, such as the lack of validation across different education systems, small sample sizes, and the need for improved handling of sequential data and course relationships.

In the context of domestic studies in Vietnam, the application of ML in education is still in its early stages. Notable works have focused on using ML for course selection, academic performance prediction, and identifying at-risk students. Additionally, many studies in Vietnam have faced challenges related to small sample sizes and the need for more comprehensive models that account for both structured and unstructured data.

Research gaps: Current methods rely on static data and traditional ML, making it difficult to capture the sequential nature of learning. Challenges include small, fragmented datasets and missing temporal context. Future research should focus on building standardized sequential datasets and developing hybrid DL models suited to diverse educational data.

1.4. Datasets

HNMU1 Dataset: Collected from HNMU (2021–2022), includes 2,763 records of Primary Education students; after preprocessing, 933 records with 39 attributes remain. ***HNMU2 Dataset:*** From HNMU (2023–2024), with 2,613 records of Math and Physics Education students; after cleaning, 551 Math student records with 88 attributes are retained. ***VNU Dataset:*** Survey-based data from Literature Education students at VNU (2023), with 521 records and 91 attributes; 271 samples are labeled. ***International Datasets:*** Five datasets from various global institutions were also used.

Privacy Challenges: Educational data often contain sensitive personal and behavioral information. Issues like inconsistent curricula, frequent updates, and varying digitization levels hinder standardization. Research must ensure privacy, consent, and model adaptability to small, diverse datasets.

1.5. Evaluation metrics for predictive models: Classification models are evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. For regression models, key metrics include MSE, RMSE, MAE, and R^2.

CHAPTER 2. EARLY PREDICTION OF SEMESTER GRADE POINT AVERAGE USING DEEP LEARNING APPROACHES

In modern education, predicting students' semester Grade Point Average (SGPA) is important for tracking learning outcomes, identifying students at risk, and guiding personalized study plans. However, SGPA is not an exact or stable measure. It can change over time under the influence of many factors, such as grading methods, teaching approaches, students' mental conditions, and differences between institutions. Therefore, SGPA should be considered a flexible indicator that reflects both uncertainty and variability. From this view, this chapter presents predictive models that apply deep learning together with uncertainty-based methods to improve accuracy and better represent the complexity of real educational environments.

Two modeling approaches are proposed. ***NeutroDLs****: Embeds neutrosophic logic into standard deep learning models.* ***NeutroGNT****: A hybrid model combining Transformer, CGAN, and neutrosophic representation to handle data imbalance and uncertainty. Experiments on seven real datasets show that the models significantly improve prediction accuracy, with NeutroGNT achieving MSE = 0.018 and R^2 = 96.05%. The content of this chapter is based on the publications [CT5] and [CT6].*

2.1. Introduction

Evaluating student performance is complex due to uncertainty in assessments, diverse grading standards, and influences like teaching styles and student psychology. The rise of online learning adds further variability through digital interaction metrics. These factors make educational data noisy and hard to standardize, limiting traditional ML/DL models. To address this, the dissertation integrates fuzzy and neutrosophic logic into DL models, with neutrosophic logic adding an indeterminacy component for better handling of uncertain and incomplete data.

2.2. Overview of Neutrosophy theory

Definition 2.1. A neutrosophic set (NS) A, defined on the universe of discourse X and denoted generally by x, can be represented in following form:

$$A = \{(x, T_A(x), I_A(x), F_A(x)) : x \in X\} \quad (2.1)$$

where each element x in the set X is associated with three membership functions: the truth membership function, $T_A: X \to [0;1]$; the indeterminacy membership function, $I_A: X \to [0;1]$; and $F_A: X \to [0;1]$: the falsity membership function. The sum of these membership values must satisfy the condition $0 \le T_A(x) + I_A(x) + F_A(x) \le 3$ for all $x \in X$.

2.3. Problem formulation

Let X be nonempty subset in R^m. $x = (x_1, x_2, \dots, x_m) \in X$. In this chapter, the dissertation investigates the following three scenarios:

Case 1: Predict the learning outcomes of the nth semester if the learning outcome of the $n-1$ semester is given. That is, knowing the value of x_{n-1}, predict the value of $x_n, 1 < n \leq m$.

Case 2: Predict the student's nth term learning results when the learning results of the previous 2 semesters are given. That is, knowing the values of x_{n-2}, x_{n-1}, predict the value of $x_n, 2 < n \leq m$.

Case 3: Predict the student's nth semester learning results when knowing the learning results of the previous 3 semesters. That is, knowing the value of $x_{n-3}, x_{n-2}, x_{n-1}$, predict the value of $x_n, 3 < n \leq m$.

2.4. NeutroDL models

Focus on the SGPA prediction problem, this dissertation proposes a novel approach that integrates these uncertainty theories into DL models to improve prediction accuracy, especially with incomplete or ambiguous educational data.

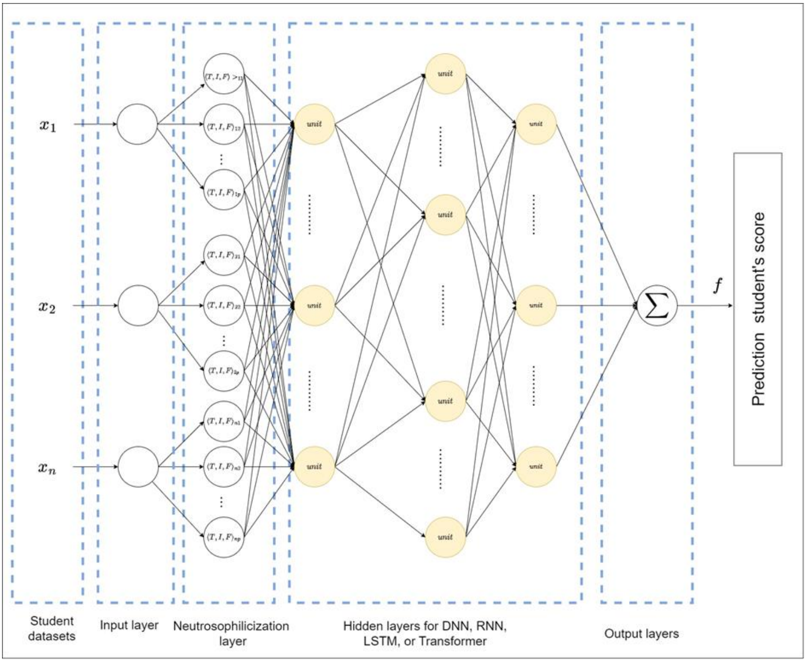

Figure 2. 4. The NeutroDL models

Figure 2.4 illustrates the general architecture of the neutrosophic neural networks (DNN, CNN, RNN, LSTM, and Transformer). The data is processed using neutrosophic functions to model uncertainty, enhancing prediction accuracy. Each data sample is characterized by a vector of 18 attributes, with 6 neutrosophic factors corresponding to performance levels. By accounting for uncertain factors, the proposed models aim to offer more flexible and realistic evaluations of student performance.

Algorithm 1. NeutroDLs - SGPA prediction with Neutrosophic logic and Deep learning models

Input: X are Historical student records; H is prediction horizon;
    F_n: Neutrosophic membership functions;
    Model ∈ {DNN, CNN, RNN, LSTM, Transformer};
    Hyperparameters: learning rate η, dropout rate d, epochs E
Output: $\hat{y}$ Predicted student performance score
Preprocess the raw student data: clean, normalize, order by time
For each input $x_i \in X$ **do**
Encode x_i using neutrosophic trapezoidal function:

$$[\mathrm{T}(x_i), \mathrm{I}(x_i), \mathrm{F}(x_i)] \leftarrow F_n()$$

end for
Construct model with:
    Input layer (neutrosophic vector $[T, I, F]$)
    Encoder (neutrosophic transformation)
    Hidden layers based on selected model (model ∈ {DNN, CNN, RNN, LSTM, Transformer})
    Decoder (neutrosophic defuzzification)
    Output layer (regression head)
Train the model using Adam optimizer with MAE loss
Run training for E epochs on training data
Evaluate model on test data using RMSE, MAE, R^2
Return $\hat{y}$

The data used in this chapter is HNMU1. Six neutrosophic sets are used: Excellent, Very Good, Good, Medium, Poor, and Very Poor. The DL methods employed for data analysis include classical DNN, CNN, RNN, LSTM, and Transformer models. Comparison results estimate the errors (average after 10 tests) of the algorithms as shown in Table 2.9.

Table 2. 9. Average error comparison for cases 1, 2, 3

Model/Metric		**RMSE**		**MAE**		**R² (%)**	
		Real input	**Neutro. Approach**	**Real input**	**Neutro. Approach**	**Real input**	**Neutro. Approach**
Case 1	**DNN**	1.06 ± 0.33	**0.89** ± 0.09	1.07 ± 0.11	**0.75**± 0.06	48.26 ± 32.00	12.76 ± 4.90
	CNN	0.92 ± 0.06	**0.90**± 0.07	**0.73** ± 0.04	0.74± 0.04	8.52 ± 4.65	**11.40** ± 5.06
	RNN	**0.89**± 0.05	0.92 ± 0.07	**0.72**± 0.04	0.73 ± 0.04	12.6 ± 8.49	12.39 ± 6.06
	LSTM	**0.90** ± 0.05	0.91 ± 0.07	0.74 ± 0.03	**0.74** ± 0.04	9.72 ± 5.39	**12.73** ± 4.97
	Transformer	0.90 ± 0.04	**0.89** ± 0.08	0.74 ± 0.03	**0.74** ± 0.04	26± 5.40	**13.13** ± 7.65
Case 2	**DNN**	1.10 ± 0.11	**0.57** ± 0.05	1.13±0.12	**0.47** ± 0.05	186.07 ± 19.20	**48.42** ± 5.74
	CNN	**0.53** ± 0.05	0.58 ± 0.04	**0.41** ± 0.03	0.46 ± 0.02	46.39 ± 6.51	**47.03** ± 5.80
	RNN	**0.55** ± 0.07	0.60 ± 0.05	**0.42** ± 0.05	0.45 ± 0.03	37.12 ± 18.19	**46.16** ± 6.82
	LSTM	**0.52** ± 0.04	0.57 ± 0.04	**0.40** ± 0.03	0.45 ± 0.03	**52.42** ± 9.95	49.51 ± 5.40
	Transformer	0.63 ± 0.07	**0.59** ± 0.06	0.48 ± 0.04	**0.47** ± 0.06	26.83 ± 5.96	**45.54** ± 8.92
Case 3	**DNN**	2.44 ± 0.16	**0.87** ± 0.05	2.31 ± 0.16	**0.74** ± 0.04	-211.39 ± 75.45	**59.45** ± 4.00
	CNN	0.86 ± 0.08	**0.80** ± 0.08	0.67 ± 0.07	**0.62** ± 0.07	59.01 ± 7.00	**62.04** ± 5.36
	RNN	0.82 ± 0.13	**0.80** ± 0.08	0.62 ± 0.12	**0.60**± 0.06	60.69 ± 9.20	**62.14** ± 7.67
	LSTM	0.88 ± 0.13	**0.76** ± 0.11	0.71 ± 0.15	**0.59** ± 0.07	58.51 ± 1.54	**65.28** ± 8.93
	Transformer	0.93± 0.07	**0.79** ± 0.06	0.77 ± 0.06	**0.59** ± 0.05	53.05 ± 7.60	**65.95** ± 4.33

The numerical results that are highlighted in "bold" indicate that the corresponding forecasting method has better results than the other method. Three case studies of HNMU1 dataset showed that the proposed approach outperformed traditional neural network approaches when working with real numbers. The RNN and Transformer models, as used in the dissertation, consistently yielded better results than other models in the same experimental setup.

2.5. NeutroGNT model

This section proposes a hybrid DL framework that integrates the Transformer, Conditional GAN (CGAN), and neutrosophic input representation. A noise-injection strategy is also introduced to improve model generalization.

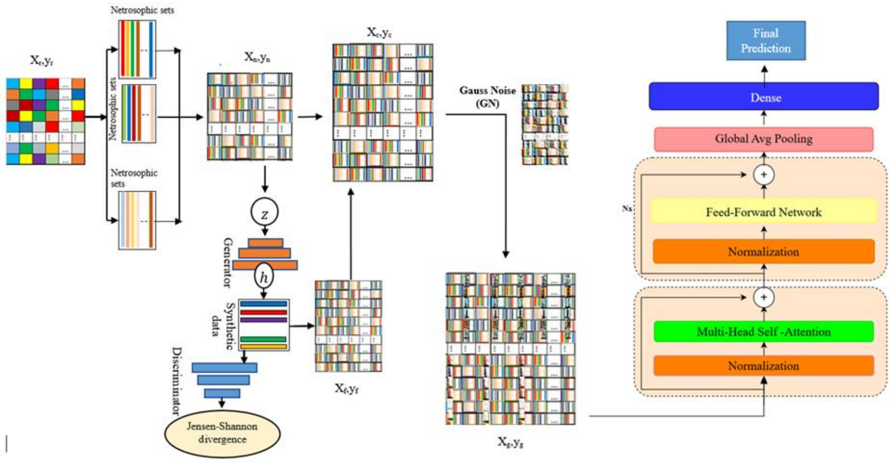

Figure 2. 10. NeutroGNT model

The functioning of the model illustrated in Figure 2.10 is as follows: Given the real dataset (X_r, y_r), we apply trapezoidal neutrosophic functions to capture uncertainty, indeterminacy, and inconsistency in the data to construct a new dataset denoted as (X_n, y_n). To fully leverage DL effectiveness, we further incorporate a CGAN to generate synthetic samples and augment the training dataset, forming (X_f,y_f). The two datasets (X_n, y_n) and (X_f,y_f) are then concated to form (X_c, y_c). On this consolidated dataset (X_c, y_c), a noise-injection strategy is incorporated to improve the robustness and generalization capabilities of the predictive model, forming (X_g,y_g). The Transformer model operates combined to capture complex patterns and dependencies within the data (X_g,y_g). Finally, performs defuzzification to convert neutrosophic values back to real values and outputs the final prediction.

Algorithm 2. NeutroGNT - SGPA prediction with Neutrosophic logic, CGAN, Noise-injection strategy and Transformer

Input: D_{real}: Real dataset of student academic records and SGPA
Z : Latent noise vector for CGAN
G : Number of synthetic neutrosophic samples to generate
T_{Neutro}: Transformer model with neutrosophic encoding and noise injection
Output: $\hat{Y}$: Predicted SGPA values for test set

$[X_r, y_r] \leftarrow$ Preprocess(D_{real}) ▷ Clean, scale, sort by semester
$X_{Neutro} \leftarrow$ NeutrosophicTransform(X_r) using trapezoidal membership functions
$[G_{CGAN}, D_{CGAN}] \leftarrow$ Train CGAN($[X_{Neutro}, y], Z$)
for $i = 1$ **to** G **do**
    $z_i \leftarrow$ Sample(Z)
    $y_i \leftarrow$ SampleLabelDistribution(y_r)
    $X_f[i] \leftarrow G_{CGAN}(z_i, y_i)$ ▷ Generate synthetic neutrosophic input
    $y_f[i] \leftarrow y_i$
end for
$D_{aug} \leftarrow$ Concatenate($[X_{Neutro}, y_r], [(X_f, y_f])$)
$D_{aug} \leftarrow$ InjectNoise(D_{aug}) ▷ Gaussian noise injection
$T_{Neutro} \leftarrow$ TrainTransformer(D_{aug})
$\hat{Y} \leftarrow$ Predict(T_{Neutro}, X_{test})
return $\hat{Y}$

Results and discussions

In this section, we use 06 datasets.

	Name	**M**	**S**	**K**	**Case**	**Input feature**	**Output**
1	HNMU2	551	52	88	1	GPA Semester 1	SGPA2
					2	GPA Semester 1, GPA Semester 2	SGPA3
					3	GPA Semester 1, GPA Semester 2, GPA Semester 3	SGPA4
2	VNU	271	43	91	2	GPA Semester 1, GPA Semester 2	SGPA3
					3	GPA Semester 1, GPA Semester 2, GPA Semester 3	SGPA4
3	Malaya-Stud	493	4	16	3	HSC, SSC, Last	Overall
4	Portugal-Math	395	3	33	2	G1, G2	G3

5	Portugal-Lang	649	3	33	2	G1, G2	G3
6	Covenant-Priv	1841	6	9	3	First Year GPA, Second Year GPA, Third Year GPA	Fourth Year GPA

Data's name, Sample size (M), Number of score-related features (S), the total of features (k)

Prior to experimentation, all records were preprocessed to remove missing values and eliminate scores outside the 0-10 range. The datasets were then split into 80% for training and 20% for testing.

The experimental results (averaged over 10 runs) indicate that the NeutroGNT model consistently outperforms all other evaluated models.

Table 2.7. Demonstrated errors for HNMU2 (averaged over 10 runs - case 1)

	Real_T	**Neutro_T**	**NeutroCT**	**NeutroGNT**
MSE	0.519 ± 0.028	0.474 ± 0.040	0.469 ± 0.031	**0.458 ± 0.011**
MAE	0.576 ± 0.014	0.560 ± 0.029	0.558 ± 0.022	**0.548 ± 0.010**
R^2	-0.087±0.058	0.008 ± 0.085	0.017 ± 0.064	**0.041 ± 0.022**

In Table 2.7, NeutroGNT achieved the lowest MSE (0.458 ± 0.011) and a 12.8% improvement in R^2 compared to the Real_T model; however, the R^2 value remains low (0.041 ± 0.022), indicating limited generalization and explanatory capability, particularly in real-world scenarios with high noise and uncertainty such as the HNMU2 dataset.

Table 2.8. Demonstrated errors (averaged over 10 runs – case 2)

Dataset		Real_T	Neutro_T	NeutroCT	NeutroGNT
HNMU2	MSE	0.323 ± 0.101	0.183 ± 0.024	0.208 ± 0.052	0.181 ± 0.030
	MAE	0.459 ± 0.085	0.339 ± 0.025	0.363 ± 0.053	0.338 ± 0.035
	R^2	0.077 ± 0.288	0.478 ± 0.069	0.407 ± 0.147	**0.482 ± 0.084**
VNU	MSE	0.302 ± 0.031	0.320 ± 0.042	0.321 ± 0.044	**0.260 ± 0.04**6
	MAE	0.441 ± 0.032	0.453 ± 0.039	0.451 ± 0.042	**0.381 ± 0.054**
	R^2	0.201 ± 0.083	0.153 ± 0.112	0.150 ± 0.116	**0.202 ± 0.140**
Portugal-Math	MSE	2.536 ± 2.129	1.263 ± 0.080	1.409 ± 0.135	**1.197 ± 0.074**
	MAE	1.065 ± 0.567	0.770 ± 0.069	0.844 ± 0.077	0.725 ± 0.043
	R^2	0.505 ± 0.415	0.754 ± 0.016	0.725 ± 0.026	**0.767 ± 0.014**
Portugal-Lang	MSE	0.704 ± 0.550	0.423 ± 0.014	0.435 ± 0.032	0.440 ± 0.033
	MAE	0.528 ± 0.241	0.403 ± 0.004	0.413 ± 0.027	0.425 ± 0.027
	R^2	0.711 ± 0.225	0.826 ± 0.006	0.822 ± 0.013	0.820 ± 0.013

In Case 2, the proposed models exhibit superior and stable performance across all 04 benchmark datasets. In particular, the NeutroGNT model delivers outstanding results in terms of both MSE (MAE) and R^2 metrics.

Table 2.9. Demonstrated errors (averaged over 10 runs – case 3)

Dataset		Real_T	Neutro_T	NeutroCT	NeutroGNT
HNMU2	MSE	0.212 ± 0.088	0.208 ± 0.081	0.175 ± 0.082	0.152 ± 0.025
	MAE	0.374 ± 0.078	0.382 ± 0.083	0.347 ± 0.081	0.322 ± 0.029
	R^2	0.047 ± 0.393	0.068 ± 0.364	0.216 ± 0.367	0.319 ± 0.111
VNU	MSE	0.119 ± 0.037	0.109 ± 0.041	0.121 ± 0.061	**0.088 ± 0.017**
	MAE	0.281 ± 0.039	0.271 ± 0.051	0.282 ± 0.074	**0.242 ± 0.026**
	R^2	0.549 ± 0.140	0.588 ± 0.154	0.541 ± 0.230	**0.666 ± 0.064**

Malaya – Stud	MSE	0.495 ± 0.563	**0.342 ± 0.03**8	0.412 ± 0.063	0.400 ± 0.055
	MAE	0.505 ± 0.249	**0.434 ± 0.025**	0.485 ± 0.048	0.473 ± 0.036
	R^2	0.788 ± 0.241	**0.854 ± 0.016**	0.824 ± 0.027	0.829 ± 0.024
Covenant - Priv	MSE	0.023 ± 0.001	0.022 ± 0.001	0.023 ± 0.003	**0.019 ± 0.00**2
	MAE	0.116 ± 0.003	0.114 ± 0.002	0.118 ± 0.008	**0.107 ± 0.005**
	R^2	0.949 ± 0.002	0.952 ± 0.001	0.950 ± 0.007	**0.958 ± 0.003**
	RMSE	0.152 ± 0.003	0.147 ± 0.002	0.150 ± 0.009	**0.138 ± 0.005**

Among the evaluated models, NeutroGNT stands out for achieving the best balance between accuracy and robustness. On the Covenant-PrivateEng dataset, it recorded the highest average R^2 score, clearly outperforming other models. Notably, its average RMSE is 0.138 lower than that of the Real_T model. Furthermore, it achieved a minimum RMSE of 0.1342, which is lower than the best result previously reported by Aderibigbe et al (2019). Additionally, its minimum MSE of 0.018 is the lowest across the entire study, and the maximum R^2 of 96.05% surpasses all prior benchmarks. These results confirm the superior predictive performance and effectiveness of the NeutroGNT model.

2.4. Appendix to Chapter 2: This section gives the summary of GAN, CGAN and Transformer model for the SGPA prediction task.

CHAPTER 3: ENHANCING THE PERFORMANCE OF EARLY GRADUATION CLASSIFICATION MODELS

To further improve the performance of early graduation prediction models for university students, this chapter presents two advanced hybrid deep learning models: LATCGAd and AWG-GC. Both models are designed to address the challenges of limited and imbalanced educational data by automatically augmenting training data and leveraging state-of-the-art deep learning architectures to improve predictive capability. LATCGAd combines Transformer, CGAN, and Adaptive Layer Normalization (AdaLN) to improve data quality, stabilize training, and reduce overfitting, reaching 96.97% accuracy and 73.66% F1-score. AWG-GC integrates Autoencoder, Wasserstein GAN, and Graphormer for joint representation learning, data augmentation, and classification, achieving 98.54% accuracy and 99.25% F1-score, significantly surpassing baseline models.

The contents of this chapter are based on the research presented in publications [CT7] and [CT8].

3.1. Introduction

The LAGT method, which significantly outperformed traditional models by combining GCN and Transformer architectures in a semi-supervised framework, was introduced in [CT2]. Building on this, the chapter explores recent advances in generative models (e.g., CGAN, WGAN) and graph-based architectures (e.g., GAT, Graphformer) and Transformer, which address challenges like small, imbalanced datasets. It proposes LATCGAd and AWG-GC, which integrate data generation and DL models to improve early graduation prediction with higher accuracy and robustness.

3.2. The LATCGAd model

This model uses CGAN to generate synthetic samples for underrepresented labels, addressing data imbalance. The expanded dataset is then processed by a Transformer Encoder to capture complex feature relationships. AdaLN is integrated into each Transformer layer to adapt normalization to input characteristics, reducing bias, improving convergence, and minimizing overfitting on small datasets.

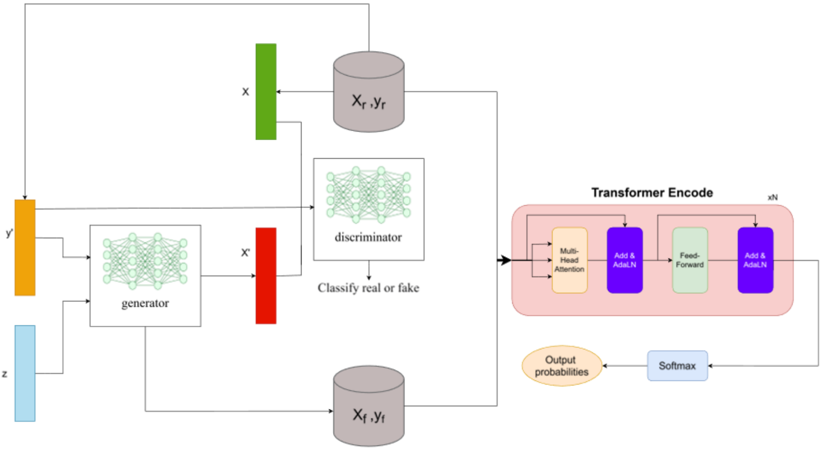

Figure 4. 1. The LATCGAd model

Algorithm 3. LATCGAd - Learning Analysis with Transformer, CGAN, and Adaptive Layer Normalization

1: Input: D_{Real}: Real dataset of labeled student features and labels
2: Z : Latent noise vector for CGAN
3: G: Number of synthetic samples to generate
4: T_{AdaLN}: Transformer model with Adaptive Layer Normalization
5: Output: Ŷ: Predicted graduation classification labels for test set

6: $[X_r, y_r] \leftarrow$ Preprocess(D_{real})
7: $[G_{\text{CGAN}}, D_{\text{CGAN}}] \leftarrow Train_{CGAN}([X_r, y_r], Z)$
8: for $i = 1$ **to** G **do**
9: $z_i \leftarrow$ Sample(Z)
10: $y_i \leftarrow$ Sample_Label_Distribution(y_r)
11: $X_f\ [i] \leftarrow G_{CGAN}(z_i, y_i)$ ▷ Generate synthetic sample
12: $y_f\ [i] \leftarrow y_i$
13: end for
14: $D_{aug} \leftarrow$ Concatenate($[X_r, y_r], [X_f, y_f]$) ▷ Augmented dataset
15: $T_{\text{AdaLN}} \leftarrow$ Train_Transformer(D_{aug})
16: Ŷ $\leftarrow$ Predict($T_{\text{AdaLN}}, X_{\text{test}}$)
17: return Ŷ

The experiment is conducted on three datasets: HNMU1, HNMU2, and VNU. The dataset is divided into train, validation, and test sets, with 60% of the data used for training, 15% for validation, and 25% for testing.

On HNMU1, LATCGAd achieves 95.56% accuracy, outperforming all baseline models. It also improves Precision (72.50%), Recall (74.78%), and F1-score (73.61%), showing strong true positive classification.

On HNMU2, LATCGAd leads in accuracy (96.97%) but lags behind DT in Precision and Recall, indicating good generalization but limited sharpness in identifying target classes.

Table 3. 1. Prediction results on the HNMU2 dataset

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
DT	89.70	94.65	79.26	82.48
SVM	80.29	41.38	41.81	40.55
LR	71.74	64.57	62.25	60.46
DNN	87.05	69.32	60.92	63.75
GAT	89.05	53.52	57.95	55.16
Transformer	95.62	72.77	60.99	64.79
LATCGAd	**96.97**	**73.26**	**74.09**	**73.66**

On the VNU dataset, LATCGAd achieves an accuracy of 87.65%, lightly outperforming DT (83.95%), and standard Transformer (86.76%).

3.3. The AWG-GC model

AWG-GC is an extended version of LATCGAd, keeping its strengths in data generation and training while adding components to handle complex features, limited labels, and multidimensional relationships in educational data. After preprocessing, the raw data forms an initial sample set consisting of $(\mathrm{L}+\mathrm{U})$ samples, where $(\mathrm{X_L}, \mathrm{y_L})$ are labeled samples and $\mathrm{X_U}$ are unlabeled samples. Note that each sample in this set has a dimensionality of n. This dataset is used to train a deep Autoencoder neural network to learn the latent space representation. At the same time, the $(\mathrm{L}+\mathrm{U})$ sample set is also used to train a WGAN to generate an additional synthetic sample set, $\mathrm{X_G}$, consisting of G new samples. This expanded sample set $(\mathrm{L}+\mathrm{U}+\mathrm{G})$ is then fed into the encoder part of the Autoencoder to extract features and reduce the data dimension from n to m. Thus, each sample in the $\mathrm{L}+\mathrm{U}+\mathrm{G}$ set has two representations: one in the original n-dimensional space and one in the m-dimensional feature space. The neighborhood graph of the samples in the $(L+U+G)$ set is built using the KNN algorithm based on this combined feature space. The resulting graph is then fed into the Graphormer model.

Using global attention mechanism weighted by graph distance, Graphormer can efficiently learn the relationships between nodes, thus improving the accuracy in predicting students' graduation classifications.

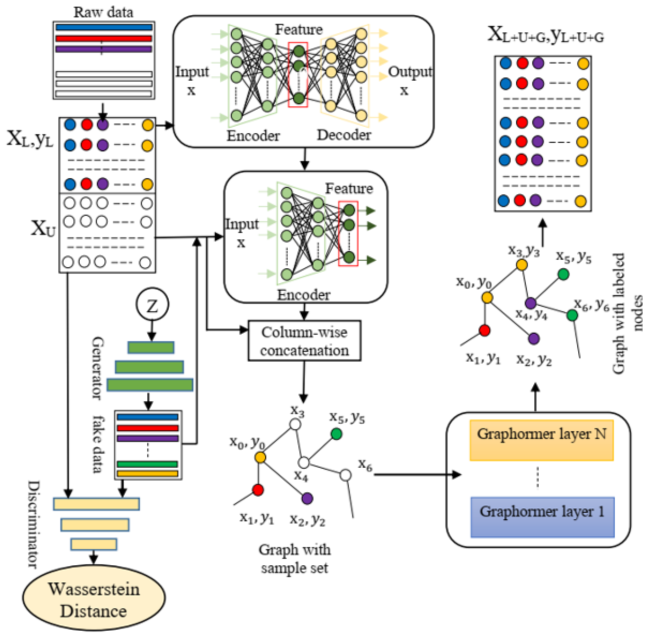

Figure 3. 1. The AWG-GC model

Algorithm 4: AWG-GC – Integrating an Autoencoder, Wasserstein GAN, and Graphormer for Graduation Classification

Input: $\mathcal{D}_{\mathrm{L}}$ **:** Labeled dataset of student features and labels
$\mathcal{D}_{\mathrm{U}}$: : Unlabeled dataset of student features
m : Number of samples in $\mathcal{D}_{\mathrm{U}}$
n : Number of samples in $\mathcal{D}_{\mathrm{L}}$
z : Latent feature dimension from Autoencoder
s : Number of synthetic samples generated by WGAN
Output: $\hat{\mathrm{Y}}$ ← Predicted graduation classification labels

$[X_L, y_L] \leftarrow$ Preprocess($\mathcal{D}_L$)
$X_{\mathrm{U}} \leftarrow$ Preprocess($\mathcal{D}_{\mathrm{U}}$)
Train Autoencoder on $X_L \cup X_U$
$Z_{\mathrm{L}} \leftarrow$ Encode(X_L), $Z_{\mathrm{U}} \leftarrow$ Encode(X_{U})
$[\mathcal{G}, C] \leftarrow$ TrainWGAN(X_L, y_L)
for $i = 1$ **to** s **do**
    $z_i \leftarrow$ SampleNoise()

$y_i \leftarrow$ SampleLabel(y_L)
$x_i^{gen} \leftarrow \mathcal{G}(z_i, y_i)$
$\mathcal{D}_S \leftarrow \mathcal{D}_S \cup (x_i^{gen}, y_i)$
end for
$\mathcal{D}_{all} \leftarrow \mathcal{D}_L \cup \mathcal{D}_U \cup \mathcal{D}_S$
$Z_{all} \leftarrow$ Encode($\mathcal{D}_{all}$)
$F_{combined} \leftarrow$ Concatenate(X_{all}, Z_{all})
$G_{knn} \leftarrow$ ConstructGraph($F_{combined}$)
Train Graphormer on (G_{knn}, y_L)
$\hat{Y} \leftarrow$ Predict(Graphormer, X_{test})
return $\hat{Y}$

We use three real datasets, HNMU2, VNU, and SATDAP, to evaluate the performance of the proposed model. The SATDAP, Portugal, consists of 4,424 records and 36 features. The HNMU2 and VNU dataset is divided into train, validation, and test sets, with 60% of the data used for training, 15% for validation, and 25% for testing. The SATDAP dataset is divided into three subsets: training, validation, and testing, with 65% of the data used for training, 15% for validation, and 20% for testing.

Table 3. 2: Prediction results on the HNMU2 dataset:

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN	80.29	40.68	41.58	40.59
RF	95.62	47.79	48.31	48.34
Transformer	95.62	72.77	60.99	64.79
GAT	89.05	53.52	57.95	55.16
Graphomer	97.08	73.45	73.97	73.67
AutoGAT	93.43	59.84	59.74	59.74
AWG_GAT	**97.08**	**98.50**	**86.41**	**90.37**
AWG-GC	**98.54**	**99.25**	**99.25**	**99.25**

Prediction results obtained on the VNU dataset: The AWG-GC model consistently outperforms all other methods across all evaluation metrics.

Table 3. 3. Prediction results obtained on the VNU dataset

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN	86.76	51.45	54.98	53.12
RF	82.35	54.03	46.91	49.39
Transformer	86.76	69.72	71.73	70.72
GAT	80.88	51.60	50.52	51.00
Graphomer	88.24	80.11	63.93	64.97
AutoGAT	85.29	74.50	58.59	53.96
AWG-GAT	**89.71**	**70.95**	**95.98**	**78.64**
AWG-GC	**94.12**	**81.67**	**97.70**	**88.17**

Results obtained on SATDAT dataset: The AWG-GC model achieved the highest overall performance across all evaluation metrics. AWG-GC outperformed XGBoost of Martins et al. (2021) by 8.81% in accuracy and 9.21% in F1-score. This comparison further underscores the superiority of AWG-GC in both predictive accuracy and balanced classification performance.

Table 3. 4. Prediction results obtained on the SATDAP dataset

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN	66.67	57.66	54.73	55.35
RF	79.32	70.78	68.65	69.37
Transformer	80.34	71.87	70.99	71.34
Graphomer	80.79	74.08	70.30	71.67
AWG-GC	**81.81**	**74.74**	**73.89**	**74.21**
XGBoost (Martin et al., 2021)	73.00	**-**	**-**	65.00

These results indicate that the integration of Autoencoder, WGAN, and Graphormer architectures enables the model to better capture the underlying structure of educational data and effectively address challenges such as small sample sizes and class imbalance.

3.4. Appendix to Chapter 3: Wasserstein GANs (WGAN) and Graphormer are introduced in this section.

CONCLUSION AND FUTURE DEVELOPMENT

A. Key contributions of the dissertation

This dissertation has addressed the challenge of predicting student academic outcomes under the conditions of uncertainty, data scarcity, and imbalance that characterize real-world educational environments.

First, for short-term SGPA prediction, the study introduced two frameworks, NeutroDL and NeutroGNT, which integrate deep learning with neutrosophic theory to handle incomplete and uncertain data. Results confirmed their effectiveness, with NeutroGNT achieving an MSE of 0.018 and R^2 of 96.05%, outperforming conventional models and supporting timely monitoring, early intervention, and personalized learning.

Building on this, the research extended to long-term graduation classification prediction. Two hybrid models were proposed: LATCGAd, which reached 96.97%

accuracy and 73.66% F1-score; and AWG-GC, which achieved 98.54% accuracy and 99.25% F1-score, surpassing baselines and demonstrating the advantages of combining generative and graph-based architectures.

In summary, the dissertation contributes by: (i) developing uncertainty-aware frameworks for SGPA prediction, (ii) designing hybrid models for robust graduation classification under imbalanced data, and (iii) constructing enriched datasets and analytical pipelines for educational applications. These advances provide practical tools to support data-driven, adaptive, and intelligent decision-making in higher education.

B. Future research directions

Based on the results achieved, the dissertation proposes several promising directions for future research:

1. Broaden prediction targets to include dropout risk, program completion, course satisfaction, and career orientation, thereby providing a more comprehensive view of students' learning trajectories.

2. Apply reinforcement learning and unsupervised learning, combined with explainable AI (XAI) techniques, to both personalize learning pathways and provide transparent, interpretable justifications that enhance trust in early intervention decisions by instructors and administrators.

3. Leverage federated learning and transfer learning to develop models that ensure predictive effectiveness and generalization capability while preserving data privacy across institutions.

4. Develop an online Learning Analytics (LA) system based on the proposed models, integrated with XAI, to deliver real-time monitoring, intuitive explanations, and actionable recommendations for both students and educators.

These directions not only extend the impact of the current research but also foster sustainable, data-driven digital transformation in higher education, toward a smart, adaptive, and transparent learning ecosystem.

LIST OF PUBLICATIONS

[**CT1**]**. Son, N. T. K.**, Bien, N. V., Quynh, N. H., and Tho, C. C. (2022). Machine learning-based admission data processing for early forecasting of students' learning outcomes. *International Journal of Data Warehousing and Mining, 18*(1). (SCIE). https://www.igi-global.com/gateway/article/313585

[**CT2**]**. Son, N. T. K.,** Quynh, N. H., and Minh, B. T. (2024). Early prediction of students' graduation rank using LAGT: Enhancing accuracy with GCN and Transformer. *Journal of Computer Science and Cybernetics, 40*(4), 299-314. https://doi.org/10.15625/1813-9663/21095

[**CT3**]**. Son, N. T. K.**, Hoa, N. H., Trang, H. T. T., and Ngan, T. Q. (2024). Introducing a cutting-edge dataset: Revealing key factors in student academic outcomes and learning processes. *VNU Journal of Science: Education Research, 40*(4). https://js.vnu.edu.vn/ER/article/view/5157.

[**CT4**]**.** Vinh, T. D., **Son, N. T. K.,** and Diep, L. N. (2025). Dataset of factors affecting learning outcomes of students at the University of Education, Vietnam National University, Hanoi. *Data in Brief, 59*, 111438. (ESCI). https://doi.org/10.1016/j.dib.2025.111438

[**CT5**]**. Son, N. T. K.**, Dat, B. V., Hoa, N. H., and Trang, H. T. T. (2025). Hybrid artificial intelligence models incorporating neutrosophy for predicting student outcomes. *Lecture Notes in Networks and Systems.* (Accepted; Scopus).

[**CT6**]**. Son, N. T. K.**, Thong, N. T., and Quynh, N. H. (2025). Neutrosophy-driven deep learning for predicting student performance. *Neutrosophic Sets and Systems, Volume 87 (2025).* (Scopus).

[**CT7**]**. Son, N. T. K**., Quynh, N. H., and Minh, B. T. (2025). Refining graduation classification accuracy with synergistic deep learning models. *Cybernetics and Information Technologies, Volume* ***25****, No 2, 2025.* (Scopus, ESCI).

[**CT8**]**. Son, N. T. K.,** Vinh, T. D., Quynh, N. H., Tao, N. Q., Hop, D. T., and Minh, B. T. (2025). Enhancing student graduation prediction with integrated deep learning under data constraints. *Data Intelligence.* (Accepted; In proof, Scopus, ESCI).