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Prediction of a university student performance by AI
"A deep Learning Based Approach"

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Abstract
In recent years, the sector has witnessed a vast shift in the direction of the adoption of Artificial Intelligence (AI) across various fields because of its fantastic potential to research huge-scale facts, identify styles, and help accurate and efficient decision-making. AI plays a vital position in enhancing overall performance, saving time and sources, and enhancing carrier fine—particularly in important sectors like education. AI algorithms vary in kind, including traditional device mastering methods including long -term memory (LSTM), multilayer Perceptron (MLP) and Conversional Neural Networks (CNN), in predicting the overall performance students. The aim of this study is to analyze the application of different deep study techniques to predict the students' performance based on the old data collected from the Department of computer science at the Faculty of Information Technology. A methodology was implemented for collecting and preprocessing student data, followed by training the models on the prepared data. The model obtained was tested the use of check information amassed from the same domain. Experimental effects showed that CNN achieved the maximum F1 Score factor of 0.9032 to improve both LSTM and MLP. Despite the minor adjustments, all models validated robust accuracy (87.5%), confirming their reliability in instructional data analysis. Additionally, a comparison was conducted among deep neural networks to highlight the differences in their performance. These findings emphasize the significant role of artificial intelligence and neural networks in advancing the

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educational process by enabling early intervention strategies and improving learning outcomes.
Keywords: Artificial Intelligence in Education, Neural Networks Student Performance Prediction, Deep Learning, LSTM, MLP, CNN.

التنبؤ بأداء الطالب الجامعي باستخدام الذكاء الاصطناعي

" نهج قائم على التعلم العميق"

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الملخص

شهد القطاع في السنوات الأخيرة تحولًا كبيرًا نحو تبني تقنيات الذكاء الاصطناعي في مختلف المجالات، وذلك بفضل قدرته الهائلة على تحليل كميات ضخمة من البيانات، واكتشاف الأنماط، ودعم اتخاذ القرارات بشكل دقيق وفعّال. يلعب الذكاء الاصطناعي دورًا محوريًا في تحسين الأداء، وتوفير الوقت والموارد، ورفع جودة الخدمات، لا سيما في القطاعات الحيوية مثل التعليم. تتعدد خوارزميات الذكاء الاصطناعي المستخدمة في هذا المجال، وتشمل أساليب التعلم الآلي التقليدية مثل الذاكرة طويلة المدى(LSTM)، والشبكة العصبية متعددة الطبقات(MLP)، والشبكات العصبية الالتفافية(CNN)، وذلك بهدف التنبؤ بأداء الطلاب. يهدف هذا البحث إلى دراسة تطبيق تقنيات التعلم العميق المختلفة للتنبؤ بأداء الطلاب، اعتمادًا على بيانات سابقة تم جمعها من قسم علوم الحاسوب بكلية تقنية المعلومات. تم اعتماد منهجية محددة لجمع البيانات ومعالجتها مبدئيًا، تلاها تدريب النماذج على البيانات المُجهزة، ثم اختبار النموذج باستخدام بيانات من نفس المصدر.
أظهرت النتائج التجريبية أن نموذج CNN حقق أعلى قيمة في مقياس F1 بلغت 0.9032، متفوقًا على كل من LSTM وMLP وعلى الرغم من الفروقات البسيطة، أظهرت جميع النماذج دقة قوية بلغت 87.5%، مما يؤكد موثوقيتها في تحليل البيانات التعليمية. كما أُجريت مقارنة بين الشبكات العصبية العميقة لتوضيح الفروقات في أدائها. تؤكد هذه النتائج على الدور الكبير الذي تلعبه تقنيات الذكاء الاصطناعي والشبكات العصبية في تطوير العملية التعليمية، من خلال تمكين استراتيجيات التدخل المبكر وتحسين مخرجات التعلم.

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الكلمات المفتاحية: الذكاء الاصطناعي في التعليم، الشبكات العصبية، التنبؤ بأداء الطلاب، التعلم العميق، الذاكرة طويلة المدى (LSTM)، والشبكة العصبية متعددة الطبقات (MLP)، والشبكات العصبية الالتفافية(CNN).

I. Introduction

Educational institutions aim to improve teaching quality and corrective results. Virtual Learning Environment (VLE) plays an important role in assessing factors affecting educational success, providing the opportunity for the informed course adjustment that matches the students' needs and progression [1]. In this context, the use of artificial intelligence (AI) increases rapidly, but a deep understanding of its systematic implementation in education is necessary. This research examines the use of artificial nervous networks (Ann) to predict academic performance and analyze various factors affecting student results [2]. Learning management systems (LMSS), such as boards, are integrated parts to monitor and evaluate the student's performance over time. In recent years, deep learning models, especially CNN-LSTM, have been used to predict student results based on their interaction in LMS, which provides more dynamic and accurate analysis than traditional methods [3]. In addition, the emergence of explaining artificial intelligence (XAI) has made significant progress in AI applications in education, which provides human supportable clarification for success or struggle for some students. This pair of interpretation gives XAI different benefits to the traditional machine learning model, so that teachers can better understand the arguments behind the predictions [4]. In the midst of innovative methods model has emerged as a more accurate alternative to traditional approaches, and provides valuable insights into relation to student behavior, performance and course design [5]. Similarly, other studies have introduced hybrid models, such as Mic, CNN, meditation mechanisms and gravel, which consider both cosmic and convenience -based dimensions, show better prediction accuracy by assessing both cosmic and practical dimensions, which increases the ability to recognize students quickly [6]. This integration of temporary and convenience -based data allows for a more comprehensive understanding of students' behavior, enabling the development of interventions that are targeted for people who require extra support [7]. In addition to these models, the use of MLP (multi -layer Perceptron), CNN (Convisional Neural Network) and LSTM (long short -term

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memory) network has proven to be important for increasing education. MLP networks help to capture non –relationships MLP networks help to capture non-relationships between different characteristics of students' learning activities, which improves the model's ability to predict results based on complex patterns. CNN, which is known for their ability to withdraw spatial functions, can be used to identify specific engagement patterns and interactions in educational materials, while LSTM is excellent in handling the data and long-lasting networking sequence of the networking sequence, Which is important for predicting the student's performance over time. These models complement each other, allow the student's achievements to predict and understand a comprehensive approach, especially in the dynamic and complex learning environment, in addition, attention-based deep learning models have shown promising results to improve the student's performance preconction. By incorporating time-sensitive information and dynamically adapting into different teaching contexts, these models provide more accurate and personal insight into the student's performance [7]. This study also presents a hybrid approach that combines PSO-DN to predagogical results, effectively recognizes students at risk and promotes improvement in educational quality [8]. It has been proposed to create a darker knowledge tracking model with a concentration mechanism, which over time increases performance performance by better evaluating knowledge acquisition of students, with a traditional model that traditional models face in capturing complex learning patterns over time [9]. Finally, the MSC transition detection network integrates CNN and transformer models to track class engagement more efficiently, leading to increased ability to monitor students' behavior in real time. This model continuously supports the improvement of educational practices and provides more accurate insight into how involvement affects students' success [10].

This paper implements intensive teaching algorithm to analyze the effectiveness of different techniques to predict the student's performance, including long-term short-term memory (LSTM), Multi-Layer Perspaptron (MLP) and Convisional Neural Network (CNN). These algorithms will be evaluated based on their accuracy and performance, and the following questions will be answered:

Q1: How can we predict a student's performance based on historical educational data and relevant characteristics?

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Q2: What factors contribute to students underperforming, and how can initial intervention strategies be implemented?
Q3: How does the knowledge of the students' background affect their latest academic performance and learning outcomes?

II. Deep learning algorithms

In this research, three deep learning models-LSTM, MLP, and CNN—are used to predict student performance based on historical academic data. LSTM, a recurrent neural network, captures sequential dependencies, making it effective for predicting trends in student learning. MLP, a feedforward neural network, maps complex relationships between academic features and performance. CNN, usually used for image processing, is used here to analyze structured data by identifying correlations between properties. These models are evaluated using MSE, F1 score and accuracy, and receive the best performance with CNN, and perform deep learning ability in educational data analysis.

III. Building the model

A. Data collection

Transcripts data for students enrolled in the General Department of the Faculty of Information Technology for the year 2024 were collected from the database management system after they completed their first semester and the total number of students was 200 students. The collected data included students' high school GPA, Age, Gap, and gender their grades in various courses during the first semester, and their place of residence.
The data was organized in a Microsoft Excel sheet and saved as a CSV file for processing in a programming language. According to faculty regulations, a student must obtain a minimum of 50% in a subject to pass; otherwise, it is considered a failure. The data was pre-processed based on faculty rules for the purpose of research. Table (1) below shows the evaluation system in Faculty of Information Technology.

Table 1. Classroom Evaluation System

Percentage		Letter Grade
From	To	
85	100	Excellent
75	84	Very Good
65	74	Good
50	64	Pass
0	49	Fail

Table (2) shows the conversion of GPA numerical values.

Table 2. Numerical Values of the GPA

Marks scored	Outcome
Score between 0-64	1
Score between 65-74	2
Score between 75-84	3
Score between 85-100	4

Table (3) shows the continuous values.

Table 3. Continues Values of the Total Marks

Subject Name	Outcome
Arabic-1	71
English-1	68
Islamic Culture	50
IT-Introduction	70
Problem-solving	62
Physics	75
Math_1	59

B. Tools Used

Many well-installed libraries were used to use deep learning algorithms to predict the student's performance. Python Software 3.12, Spider Console and Jupiter Notebook were used as a primary development environment. For deep learning models Construction and training, Tensorflow and Keras were used for algorithms such as LSTM, MLP and CNN. In addition, pitorch was used to experiment with different neural network architectures. Data processing and evaluation were performed using Scikit-Larn (Sergern), while Numpy and Pandas provide numerical operational and data management facilities. Cross verification, especially K-Fold Cross verification, was used to ensure strong model evaluation and performance stability. Vizulizing responsibilities have been executed with plotlib and seaborn, and Scipy was used for scientific and statistical calculations. These tools enabled efficient data manipulation, model training, evaluation, and visualization, which contributes to a success implementation of the research objectives.

C. Data Preparation and Pre-Processing

Initially, we removed inappropriate attributes, consisting of student name, nationality, Gap, age, and gender. We additionally eliminated facts associated with popular and optionally available guides, focusing solely on the mandatory courses from the program in the first semester. Next, we re-prepared the statistics so that each

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student had the following attributes: final GPA (GPAOB), region, and the grades for the courses taken during the study program. In the final step, we grouped the final GPA into 5 categories: excellent, very good, good, pass, and fail. Similarly, we converted the students' grades in courses into numeric values. The following Table (4) demonstrates a sample of the facts we worked with.

Table 4. Sample of Data

ID	High_School_GPA_Class	Region_ Tarhuna_Souq_Al_Ahad	Region_ Tripoli
1	3	1	0
2	2	1	0

D. Data Visualization

After loading the data to Python Software, we got some primary useful knowledge about the attributes before applying any method by using the visualizing technique in the software. There are basic features that help us to identify whether they have an impact on the level of the student by showing the features and the final Score of the student in the training and test periods used in this research to predict the final score as shown in figures of GPA and Final score (1), Address and Final score (2).

A positive correlation is observed between the GPA in high school and the performance of the university course. Students with an "excellent" GPA (4.0) typically achieve success in most courses, suggesting that a high school GPA is a strong predictor of academic performance in the first year of university. Students with a "Very Good" GPA (3.0) also succeed in a significant number of courses, although there are instances of failure in subjects such as Problem Solving and Physics. On the other hand, students with a "Good" GPA (2.0) tend to have lower success rates, facing difficulties in courses like IT Intro and Math_1, which indicates that students with lower high school GPAs are more likely to struggle in certain university subjects.

On the contrary, high school GPA plays an important role in university success; it is not the sole determining factor. Some students with "Very Good" or "Good" GPAs manage to succeed in most courses, suggesting that factors such as personal effort, study skills, and other individual attributes are also significant contributors to academic performance.

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It is clear that challenging courses for students appear to be Problem Solving, Physics, and Math_1, as they show the highest failure rates. This highlights the need for different teaching strategies or additional academic support to help students succeed in these subjects.as Shows in the Figure (1).

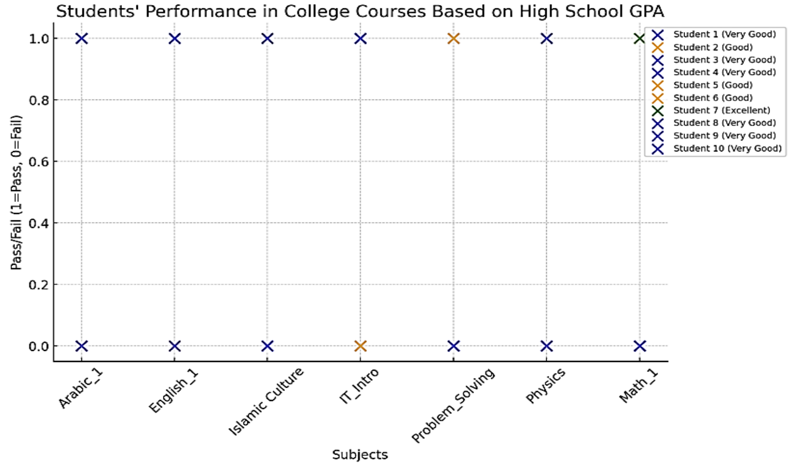

Figure 1. Correlation between GPA and final score

According to the heatmap, there is a clear variation in success and failure rates among different residential areas, suggesting that a student's place of residence may have an impact on academic performance. Some areas show higher success rates in most subjects, which could reflect a better educational environment or stronger academic support.

On the other hand, some areas exhibit higher failure rates in certain subjects, indicating disparities in prior education quality or the influence of environmental and social factors on academic achievement.

Nonetheless, residence alone cannot be considered the sole determining factor, as some subjects show consistently high failure rates across all regions. This shows difficulty of the course itself plays a crucial role, irrespective of geographic region. Therefore, even as a student's location of house may additionally in part have an effect on their instructional performance, person factors along with dedication, effort, and commitment to studying continue to be the important thing determinants of success or failure as shown in Figure (2).

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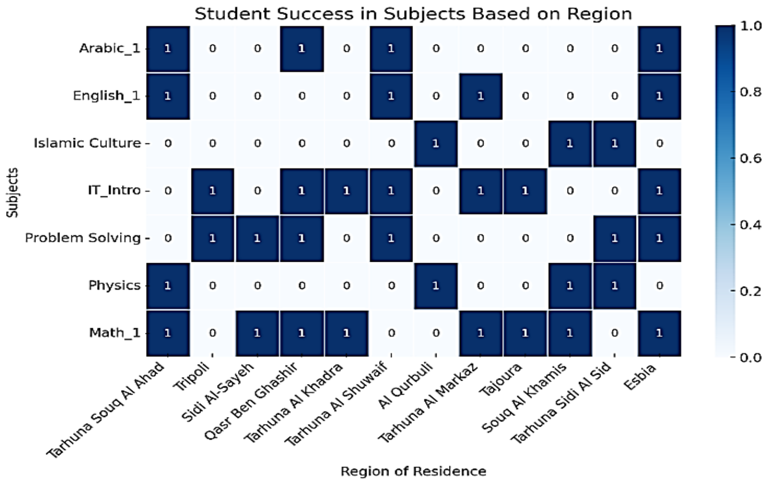

Figure 2. Final score distribution by region

IV. Experiments and Results

In this section, experiments performed will be explained in detail and the obtained results will be presented.

As it is mentioned above in this research, experiments are divided into three categories according to their Outputs as seen in Tables (5-7)

Table 5. MLP Model Performance

Algorithm	MLP Evaluation Metrics		
MLP	MSE	F1-Score	Accuracy
	0.0560	0.8276	0.8750

Table 6. LSTM Model Performance

Algorithm	LSTM Evaluation Metrics		
LSTM	MSE	F1-Score	Accuracy
	0.0574	0.8667	0.8750

Table 7. CNN Model Performance

Algorithm	CNN Evaluation Metrics		
CNN	MSE	F1-Score	Accuracy
	0.0536	0.9032	0.8750

The student's performance output in the seven courses is based on twenty-one attributes, represented as (0,1) and continuous values with similar attributes.

The evaluation of the deep learning models was performed using three key metrics: Mean Squared Error (MSE), F1 Score, and

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Accuracy. Each metric provides insights into different aspects of model performance.

A. Mean squared error experiments

MSE measures the average squared difference between actual and predicted values. A lower MSE indicates a more precise model for numerical predictions. The obtained results show that CNN achieved the lowest MSE (0.0536), followed by MLP (0.0560) and LSTM (0.0574), indicating that CNN had the least prediction errors. The MSE calculation follows equation (1), which can be seen in Figure (3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{yi})^2 \qquad (1)$$

B. F1 score experiments

The F1 Score evaluates the balance between precision and recall, which is critical for classification tasks. A higher F1 Score indicates better classification performance. The results reveal that CNN achieved the highest F1 Score (0.9032), followed by LSTM (0.8667) and MLP (0.8276). The F1 Score is calculated using equation (2), which can be seen in Figure (3).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (2)$$

C. Accuracy experiments

Accuracy measures the proportion of correctly classified instances out of the total samples. All three models achieved the same accuracy of 87.5%, indicating that while their classification correctness is similar, the quality of their classifications differs. Accuracy is determined by equation (3), which can be seen in Figure (3).

$$Accuracy = \frac{True\ Postitive + True\ Negatives}{Total\ Samples} \qquad (3)$$

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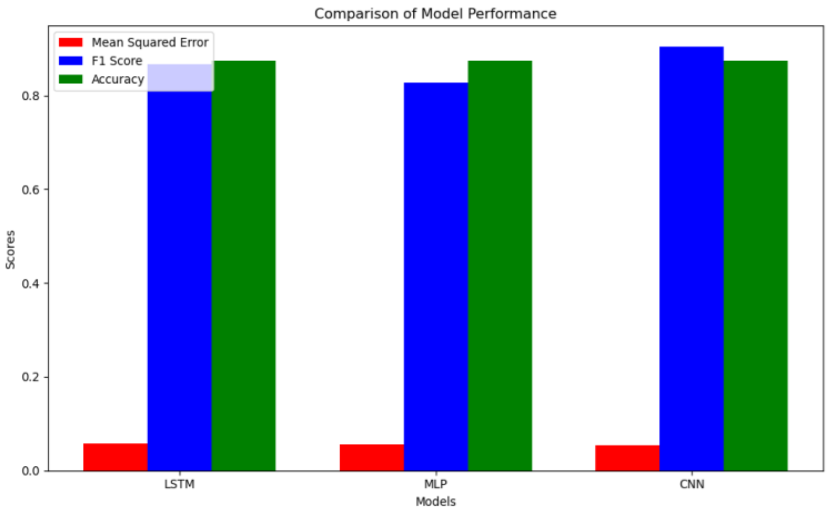

Figure 3. Performance comparison of deep learning algorithm

V. Conclusion

This research focuses on analysing the capabilities of deep Learning Algorithms (DLA) to predict the final result in first-semester courses using of historical data, which include previous information and geographic records. It specializes in the effects of numerous students inside the first-semester courses of the General Department, Faculty of Information Technology.

Three deep learning models —MLP, LSTM, and CNN—were implemented and compared based on various evaluation metrics, including Mean Squared Error (MSE), F1 Score, and Accuracy.

1- Analysing the performance of the model reveals that all models demonstrated a similar prediction accuracy of 0.8750, indicating their strong ability to classify outcomes effectively. However, the CNN model outperformed the others by achieving the lowest MSE (0.0536) and the highest F1 Score (0.9032), making it the most efficient in balancing accuracy and error minimization.

2- Comparison of model based on evaluation measurements Shows that the MLP model provided good performance with MSE = 0.0560 and F1 score = 0.8276, but it was not the best in the tested model. The LSTM model improved MLP in the form of F1 score (0.8667), but was slightly higher MSE (0.0574) which indicated a slightly low accuracy in the assessment of real values. Meanwhile, the CNN model appeared as the most stable, achieved the best F1 score and the lowest MSE, making it the most reliable for this prediction task.

3- The recommendations and future instructions obtained from this research suggest that the CNN model is best suited for future

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systems, which requires high accuracy in predicting the student's performance. Model performance can be further improved by incorporating hybrid models or by improving computer propagation techniques to ensure more accurate and stable results. In addition, a smart recommendation system based on the model's predictions can be developed to help students choose appropriate courses and suggest personal study strategies that fit their strengths and weaknesses. This approach can contribute significantly to improve general education results.

In regards to questions raised in section 2 of this papers.

A1- Deep learning models including LSTM, MLP and CNN were used to predict the student's performance based on their educational history. The results demonstrated that all models gained high accuracy of 87.5%, indicating their reliability when it comes to predicting students. However, CNN improved other models, the Mean squared error of 0.0536 (MSE) and the highest F1Socre of 0.9032, making it the most effective model to predict the student's performance.

A2- Since models effectively predict the student's performance, the student can use techniques such as SHAP or LIME to analyze the effect of various factors (e.g attendance, participation, and previous grades) on the results. If prophecies indicate that some students risk under performance, initial intervention strategies can be used, such as academic counseling, provide additional teaching resources or use teaching methods to support struggling students before they experience important educational difficulties.

A3- The effects of background knowledge can be evaluated to those without such a basis by comparing the performance of students with previous experience in programming, mathematics or related subjects. If data shows that students with a strong background work much better, it highlights the need for early programs or basic courses to help students with a lack of knowledge about knowledge. Giving these resources can increase understanding and improve their overall academic results.

The findings of this research indicate that artificial intelligence and deep learning can play an important role in identifying the most important factors for identifying important factors that affect the risk and to improve the success rate of the student.

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