Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal **Vol. 7, No. 1, January 2025, pp: 1-12; eISSN: 2656-8632**

RESEARCH ARTICLE OPEN ACCESS

Manuscript received June 22, 2024; revised August 10, 2024; accepted August 16, 2024; date of publication November 11, 2024
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v7i1.489

How to cite: Ahmed Abatal , Adil Korchi , Mourad Mzili , Toufik Mzili , Hajar Khalouki and Mohammed El Kaim Billah, "A Comprehensive Evaluation of Machine Learning Techniques for Forecasting Student Academic Success", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 7, no. 1, pp. 1-12, January 2024.

A Comprehensive Evaluation of Machine Learning Techniques for Forecasting Student Academic Success

Ahmed Abatal[1,2], Adil Korchi[1], Mourad Mzili[3], Toufik Mzili[2], Hajar Khalouki[4], Mohammed El Kaim Billah[5]

[1]Faculty of Juridical, Economic and Social Sciences, Chouaib Doukkali University, El Jadida, Morocco
[2]Departement of computer science, LAROSERI Lab, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco
[3]Departement of Mathematics, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco
[4]Departement of computer science, Faculty of Sciences and Techniques, Hassan Premier University, Settat, Morocco
[5] Department of Computer Science, ELITES Lab, ESTSB , Chouaib Doukkali University El Jadida- Morocco

Corresponding author: Toufik Mzili (e-mail: mzili.t@ucd.ac.ma)

ABSTRACT Improving academic outcomes relies on accurately anticipating student outcomes within a course or program. This predictive capability empowers instructional leaders to optimize the allocation of resources and tailor instruction to meet individual student needs more effectively. In this study, we endeavor to delineate the attributes of machine learning algorithms that excel in forecasting student grades. Leveraging a comprehensive dataset encompassing both personal student information and corresponding grades, we embark on a rigorous evaluation of various regression algorithms. Our analysis encompasses a range of widely used technniques, Incorporating various machine learning algorithms like XGBoost, Linear Regression, K-Nearest Neighbor, Decision Tree, Random Forest, and Deep Neural Network. By conducting thorough comparisons using metrics such as Root Mean Squared Error, determination coefficient, Mean Average Error and Mean Squared Error. Our aim is to pinpoint the algorithm that exhibits superior predictive ability. Notably, our experimental findings unveil the deep neural network as the standout performer among the evaluated algorithms. Having an outstanding coefficient of determination of 99.95% and Minimal error margins, the DNN emerges as a potent tool for accurately forecasting student grades. This discovery not only underscores the efficacy of advanced machine learning methodologies but also underscores the transformative potential they hold in shaping educational practices and optimizing student outcomes.

INDEX TERMS ML Algorithms, Predicting, Optimizing Data, Performance, Supervised learning, Metrics.

I. INTRODUCTION

Forecasting student academic performance [1] is a prevalent challenge within the realm of education, incorporating areas like student evaluation, curriculum development, and educational guidance. Techniques in machine learning, encompassing neural networks and linear regression offer avenues to construct predictive frameworks capable of estimating students' grades [2] using diverse inputs such as historical performance, attendance records, and examination results. These models facilitate educators in pinpointing students at risk, tailoring individualized learning interventions, and furnishing students with feedback regarding their advancement. Forecasting students' academic outcomes through machine learning algorithms typically entails several key steps, which may vary depending on the specific approach employed. However, to predict the performance of students using machine learning algorithms, several sequential steps are typically followed. Firstly, data collection and preparation involve gathering relevant information from student records, such as test scores, attendance, and past grades. Additionally, it involves ensuring the elimination of noise, rectifying errors, addressing missing values, enforcing consistency, and preprocessing data to align with the selected machine learning algorithm, thereby enabling precise analysis and modeling.

Subsequently, a suitable machine learning model is selected from various options like linear regression, decision trees, or neural networks, based on the data characteristics and prediction objectives. Following model selection, the model undergoes training where it is fed a large dataset to adjust its parameters and minimize errors between predicted and actual marks. Evaluation of the trained model's performance is then conducted using techniques such as cross-validation to assess its predictive accuracy on unseen data. Finally, the trained and evaluated model is deployed to forecast outcomes on fresh data, empowering informed decision-making within educational settings.

The primary aim of this paper is to investigate and evaluate various machine learning methodologies for predicting student academic performance, encompassing data collection, preprocessing techniques, model selection, training, and evaluation of predictive accuracy. By examining and comparing machine learning algorithms such as neural networks and linear regression, the study identifies the most effective models for accurately forecasting student outcomes. This contributes to a comprehensive methodological framework for applying these models in educational contexts. The study enhances predictive accuracy, enabling targeted interventions for at-risk students and providing actionable insights for educators and policymakers to make informed decisions on curriculum development, resource allocation, and educational support strategies.

This paper explores a variety of methodologies utilized in machine learning methods in the field of the prediction of student performance. It covers key stages incorporating data acquisition and data preprocessing, model selection, then training and evaluation process, and subsequent present the outcomes of predictions. The paper is organized as follows: a thorough review of pertinent literature will be provided, followed by an explanation of the machine learning algorithms employed. Subsequently, the methodology adopted in this study will be outlined. Finally, the paper will present the empirical findings of the predictive models and conclude with final remarks and implications.

The contribution of this study is threefold: first, it introduces the innovative application of Deep Neural Networks (DNN) in predicting student academic performance, demonstrating significant improvements in accuracy compared to traditional models; second, it provides a comprehensive evaluation of various machine learning algorithms, establishing a clear framework for model selection tailored to educational data; and third, it offers a robust methodological approach that enhances the accuracy of predictions, thereby enabling targeted interventions for at-risk students and informing data-driven decisions in educational policy and practice.

II. RELATED WORKS

Many investigations have delved into the application of machine learning to forecast academic performance. One of the commonly used methodologies is linear regression, a statistical approach utilized to identify the linear association between variable that is dependent (academic performance) and variables that are independent (test scores, attendance, and other relevant factors). Demonstrating effectiveness across various studies, linear regression has emerged as a widely utilized approach for predicting student grades [3–6]. An alternative widely used approach for forecasting student grades [7] entails employing decision tree algorithms. These algorithms con- struct a decision hierarchy model using the supplied data. Decision trees have found extensive application in predicting student grades in numerous research studies [8, 9], demonstrating effectiveness in this regard. Additionally. Apart from decision trees and linear regression, additional machine learning algorithms employed for grade prediction encompass k-nearest neighbor (KNN) [10, 11] and random forests [12]. These methods have demonstrated effectiveness in predicting student grades, while they exhibit distinctive strengths and limitations contingent upon the attributes of the data and the predictive objectives. In a particular study [13], researchers explored the application of various ML algorithms: ANN, DT, artificial neural networks, logistic regression, and na ̈ive Bayes, to forecast students' performance based on internet usage for learning and time spent on social networks. Among these, the ANN model exhibited the highest accuracy, achieving approximately 80In another investigation [14], scholars employed a deep neural network model, specifically the "BiLSTM" [15] (Bidirectional Long Short-Term Memory) Employing an attention mechanism alongside, the "BiLSTM" model was utilized for predicting students' grades based on past data. findings indicate that The BiLSTM model integrating the attention mechanism attained significant accuracy, achieving a score of 91.15Likewise, in an independent investigation [16], A deep learning framework was utilized to forecast students' academic performance, utilizing a dataset encompassing various factors such as educational characteristics, social, and demographic prior academic performance[17] were considered. To address imbalanced data issues, the synthetic minority oversampling (S.M.O.T.E) technique was employed, resulting in an approximately 96% accuracy in grade prediction across various courses. Furthermore, in [18], researchers examined two distinct datasets to forecast and categorize student performance employing a range of ML algorithms, including Support Vector Regression (SVR), Backpropagation, Gradient Boosting Classifier, Long-Short Term Memory (LSTM), and. Among these, the regression model of SVR displayed superior performance, attaining an R-squared score of 82,95% in the prediction of grades. On the other hand, for classification tasks, the Backpropagation model demonstrated the highest accuracy, reaching 86.98%.

III. METHODOLOGY

Machine learning models encompass a diverse set of algorithms and techniques aimed at enabling computers to make predictions by learning from initial data and making decisions autonomously. These models, categorized into supervised, unsupervised, and reinforcement learning paradigms, range from linear regression and decision trees to deep neural networks and reinforcement learning agents. With applications spanning across domains like finance, healthcare, robotics, and digital marketing [19–22], machine learning models continue to drive innovation, automation, and insights by extracting patterns and knowledge from vast datasets collected by ourselves, ultimately shaping the future of artificial intelligence [23, 24].

In this study, we employ several machine learning models to predict house prices. The models used are Linear Regression, Random Forest Regressor, XGBoost Regressor, Decision Tree Regressor, K-Nearest Neighbors Regressor, and Deep Neural Network. Each model is described below along with the corresponding mathematical formulations.

A. Linear Regression

Linear Regression is a fundamental algorithm for regression problems [25]. It models the relationship between a dependent variable y and one or more independent variables $x_1, x_2, \dots, x_n$ by fitting a linear equation to the observed data. The equation for Linear Regression is given by Eq. (1) [25] :

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon \tag{1}$$

where β_0 is the intercept, $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients, and ϵ is the error term.

B. Random Forest Regressor

Random Forest Regressor is an ensemble learning method that operates by constructing multiple decision trees during training and outputting the mean prediction of the individual trees. The prediction $\hat{y}$ for an input x is given by Eq. (2) [25]:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} h_i(x) \tag{2}$$

where $h_i(x)$ is the prediction of the i-th tree, and N is the total number of trees.

C. XGBoost Regressor

XGBoost Regressor (eXtreme Gradient Boosting) is an optimized gradient-boosting machine learning library designed for high performance. The objective function of XGBoost includes a regularization term to prevent overfitting Eq. (3) [24]:

$$Obj\ (\theta) = \sum_{i} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k) \tag{3}$$

where l is a differentiable convex loss function that measures the difference between the prediction $\hat{y}_i$ and the target y_i, and Ω is a regularization term.

D. Decision Tree Regressor

Decision Tree Regressor splits the data into subsets based on the value of input features. The splits are chosen to minimize the sum of squared errors (SSE) within each subset. The objective is to find splits that minimize Eq. (4) [24]:

$$R_t = \sum_{i \in t} (y_i - \bar{y}_t)^2 \tag{4}$$

where R_t is the residual sum of squares for a node t, y_i is the actual value, and $\bar{y}_t$ is the mean value of the node.

E. K-Nearest Neighbors Regressor

K-Nearest Neighbors (KNN) Regressor predicts the value of a new data point based on the values of its k nearest neighbors. The distance metric, typically Euclidean distance, is calculated as Eq. (5) [24]:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2} \tag{5}$$

where x is the input vector, x_i is the i-th neighbor, and n is the number of features.

F. Deep Neural Network

Deep Neural Networks (DNN) consist of multiple layers of neurons, where each layer transforms the input data using a set of weights and biases. The transformation for each layer l is given by Eq. (6) [24]:

$$a^{(l)} = g\left(W^{(l)} a^{(l-1)} + b^{(l)}\right) \tag{6}$$

where $a^{(l)}$ is the activation of layer $l, W^{(l)}$ are the weights, $b^{(l)}$ are the biases, and g is the activation function.

G. Evaluation Metrics

To evaluate the performance of the models, we use several metrics:

Root Mean Squared Error (RMSE) : a widely used metric in regression analysis to measure the difference between predicted and actual values. RMSE is calculated as the square root of the mean of the squared differences between actual and predicted values (as showing in Eq.(7)). A lower RMSE indicates better predictive accuracy [24]:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{7}$$

Mean Absolute Error (MAE) : is another evaluation metric used in regression analysis to measure the average magnitude of errors in predictions, without considering their direction The equation for **MAE** is given by Eq. (8) [25].

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{8}$$

Coefficient of Determination (R^2) : is a statistical measure that indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It is used to assess the goodness-of-fit of a regression model. The formula for R2 is given by Eq. (9) [25]:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{9}$$

In these equations, N is the number of data points, y_i is the actual value, $\hat{y}_i$ is the predicted value and $\bar{y}$ is the mean of the actual values, These metrics provide a comprehensive evaluation of the predictive performance of the models.

IV. USED APPROACH

In machine learning research, a robust methodology is imperative, outlining the sequence of steps essential for obtaining meaningful results. This approach clarifies the procedures, starting from data gathering and preprocessing to selecting models, training, and evaluating them, and result interpretation. By meticulously detailing each step, researchers ensure the integrity and reproducibility of their findings, laying the groundwork for advancing knowledge and innovation in the field of machine learning.

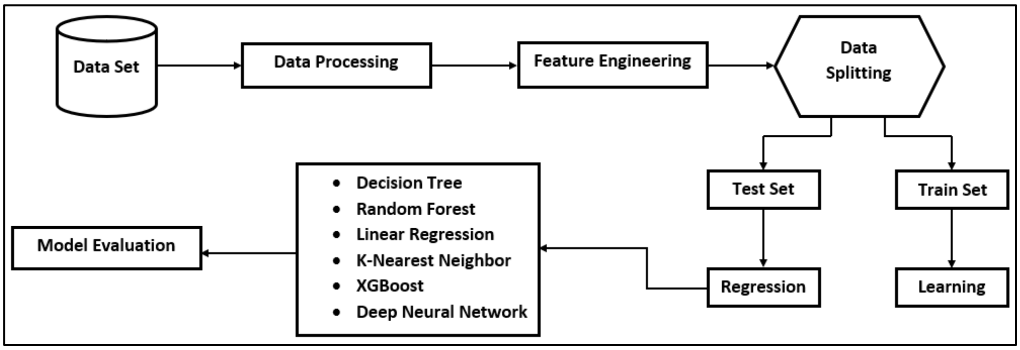


FIGURE 1. The study's pipeline

A. Data set description

This section offers an overview of the dataset employed in this investigation. The objective is to forecast students' overall scores through the application of ML and DL methodologies. To facilitate this goal, a dataset comprising details on approximately 1200 student attributes was employed. These attributes encompassed factors such as parental education level, lunch arrangements, gender, and participation in test prep courses. Additionally, the dataset incorporated scores obtained in math, reading, and writing examinations, as delineated in TABLE 1. Further details regarding the dataset are presented in the TABLE 2.

TABLE 1
Example of dataset used

Gender	Race / Ethnicity	Parental level of education	Lunch	Test preparation course	Math score	Reading score	Writing score
female	group B	bachelor's degree	standard	none	72	72	74
female	group C	some college	standard	completed	69	90	88
female	group B	master's degree	standard	none	90	95	93
male	group A	associate's degree	free/reduced	none	47	57	44
male	group C	some college	standard	none	76	78	75
female	group B	associate's degree	standard	none	71	83	78
female	group B	some college	standard	completed	88	95	92
male	group B	some college	free/reduced	none	40	43	39
male	group D	high school	free/reduced	completed	64	64	67
female	group B	high school	free/reduced	none	38	60	50
male	group C	associate's degree	standard	none	58	54	52

TABLE 2
Dataset information

	Math score	Reading score	Writing score
count	1000.000	1000.000	1000.00
mean	66.089	69.169	68.054
std	15.163	14.601	15.196
min	0.000	17.000	10.000
25%	57.000	59.000	57.750
50%	66.000	70.000	69.000
75%	77.000	79.000	79.000
max	100.000	100.000	100.000

B. Preprocessing data

Processing data in the context of machine learning involves a series of steps aimed at preparing raw data for analysis and model training [26]. This process typically includes tasks such as data cleaning to handle missing or erroneous values, feature selection or extraction to identify relevant variables, and normalization or scaling to ensure uniformity across data features. Additionally, data processing may involve encoding categorical variables, handling outliers, and splitting the dataset into training and testing subsets. By effectively processing data, machine learning models can learn from high quality input, leading to more accurate and reliable predictions. The initial phase of our analysis involved data cleaning and preprocessing. This encompassed addressing missing values, converting categorical variables into numerical representations (as illustrated in TABLE 3), and normalizing the data to guarantee uniformity across all variables.

TABLE 3
Categorical variables conversion

Gende male	Race/ ethnicity group B	race/ ethnicity group C	race/ ethnicity_ group D	race/ ethnicity_ group E	parental level of education _bachelor's degree	parental level of education high school	parental level of education_ master's degree	parental level of education_ some college	parental level of education_ some high school	lunch_ standard	test preparation course_ none
0	1	0	0	0	1	0	0	0	0	1	1
1	0	1	0	0	0	0	0	1	0	1	0
2	1	0	0	0	0	0	1	0	0	1	1

C. Optimizing Data

Optimizing Data process involves crafting, selecting, and transforming input variables to provide the most relevant information for predictive tasks. By carefully engineering features, data scientists aim to enhance the precision and resilience of ML models, ultimately driving better decision-making and insights from data. To boost the effectiveness of the ML algorithms, we conducted feature manipulation on the dataset [27]. This entailed selection of pertinent features and the creation of a new feature, termed" Total score," which served as the target variable. This was achieved by amalgamating the existing scores in reading, and writing of mathematics, as depicted in TABLE 4. The aim of feature engineering is to provide the machine learning algorithms with a more robust and predictive dataset, as depicted in TABLE 5.

TABLE 4
Establishment of the target variable named "total score."

gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score	Total score
female	group B	bachelor's degree	standard	none	72	72	74	218
female	group C	some college	standard	completed	69	90	88	247
female	group B	master's degree	standard	none	90	95	93	278
male	group A	associate's degree	free/reduced	none	47	57	44	148
male	group C	some college	standard	none	76	78	75	229
female	group B	associate's degree	standard	none	71	83	78	232
female	group B	some college	standard	completed	88	95	92	275
male	group B	some college	free/reduced	none	40	43	39	122
male	group D	high school	free/reduced	completed	64	64	67	195
female	group B	high school	free/reduced	none	38	60	50	148
male	group C	associate's degree	standard	none	58	54	52	164

TABLE 5
The ultimate dataset

gender_male	racelestinicity group B	race/ethricity group C	racelethnicity group D	raceledinicity group E	parental level of education bachelor's degree	parental level of education_master's degree	parental level of education_some college	parentalievel of education_some high school	lunch h_standard	test preparation course_none	mach score	reading score	writing score	Total score
0	1	0	0	0	1	0	0	0	1	1	72	72	74	218
1	0	1	0	0	0	0	1	0	1	0	69	75	88	247
2	1	0	0	0	0	1	0	0	1	1	90	85	93	278

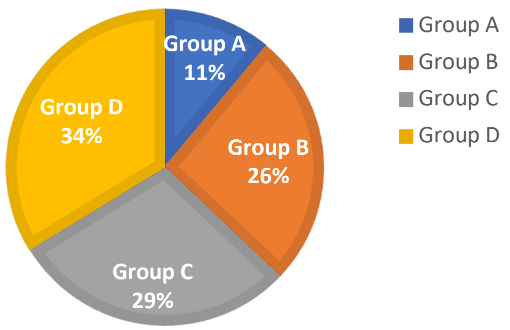


FIGURE 2. **Race / ethnicity distribution**

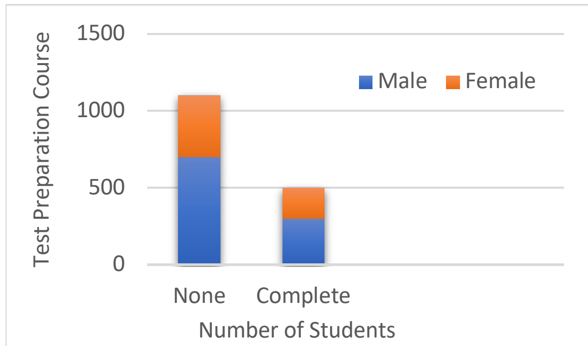


FIGURE 3. **Distribution of" gender" variable based on the" test preparation course".**

D. Data Visualization

Data visualization serves as a powerful tool in the realm of data analysis, offering a visual representation of complex information to facilitate understanding and insight discovery [28]. Through graphical means such as charts, graphs, and maps, data visualization transforms raw data into intuitive visuals, enabling analysts and decision-makers to discern patterns, trends, and relationships within the data. By presenting information in a visually engaging and comprehensible manner, data visualization plays a crucial role in conveying findings, driving decision-making, and uncovering actionable insights from data. In this study, data visualization techniques were utilized to delve into the dataset, investigating correlations among diverse variables and revealing underlying patterns or trends. Through this analysis, Essential features for forecasting students' overall scores were recognized. FIGURE 2, FIGURE 3 and FIGURE 4 showcase graphical representations of the dataset, offering visual insights into distinct parameters

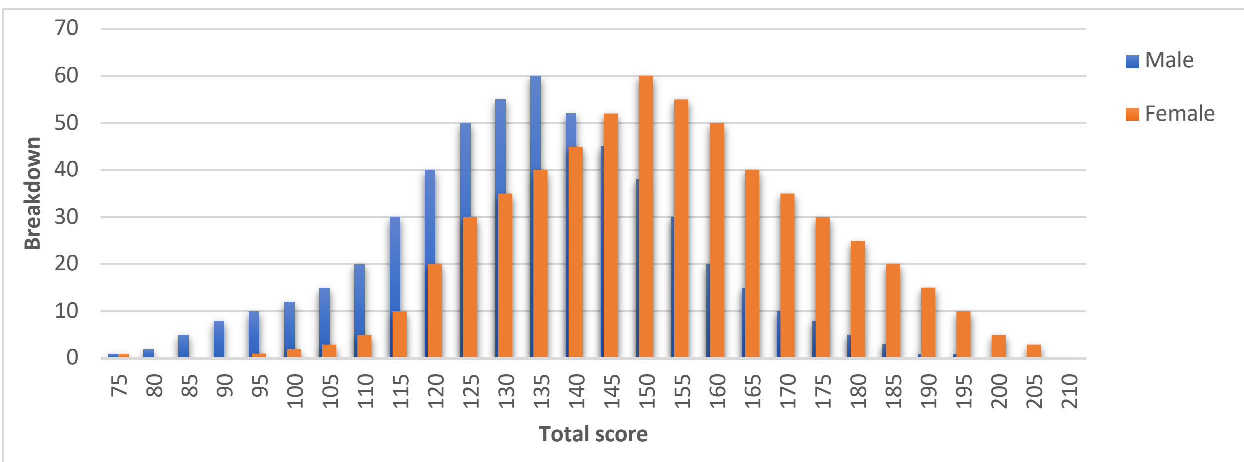


FIGURE 3. **Breakdown of total-scores by gender**

E. Correlation study

A correlation represents a statistical summary indicating the relationship between two sets of variables. It serves as a fundamental component of data exploration and is integral to various advanced machine learning methodologies. Correlation coefficients serve to quantify the degree of the linear relationship between two variables. A coefficient greater than zero signifies a positive relationship, whereas a negative value indicates a negative relationship. Values near zero suggest a weak association between the variables under consideration. Understanding negative correlation, or inverse correlation, is crucial in constructing diversified portfolios aimed at mitigating portfolio volatility. Due to the time-consuming nature of calculating correlation coefficients, data is frequently inputted into calculators, computers, or statistical software to determine the coefficient. Python offers powerful tools for calculating correlation coefficients. The correlation methods provided by libraries such as SciPy, NumPy, corr(), pearsonr() and pandas are efficient, thorough, and extensively documented. Figure 5 illustrates a robust correlation within the set of variables: reading and writing mathematic and the Total score as the target variable.

F. Dataset Partitioning in Machine Learning

The dataset was partitioned into two subsets: a testing set and a training set, using a ratio of 30/70 to maintain the validity of our results. The testing set was utilized to assess the performance of the models trained on the training set using ML algorithms. We utilized a range of ML algorithms to forecast student grades, including XGBoost, RF, KNN, DT, DNN, and LR. The implementation of these algorithms utilized the Python programming language (scikit-learn library) and following the outlined procedures. In the execution of ML algorithms, we begin by instantiating the corresponding class for each algorithm from scikitlearn library. We set any desired hyperparameters, ensuring reproducibility of results with the random state parameter. Subsequently, The model is trained using the data by employing the fit() method, which adjusts internal parameters to align with the data, using the training data and target variables as inputs. This iterative process is replicated for each algorithm. And after these last ones have completed training, It's the process of making predictions on the testing data that takes place. To implement DNN with the Keras library in Python, we start by creating a model instance utilizing the sequential neural network models. This enables us to construct a sequential arrangement of layers, where each layer processes input sequentially, subsequent layers receive the output of the preceding layer as input. Supplementary layers are incorporated into the model using the"model.add()" method, configuring 13 layers with specific numbers of neurons and activation functions. Throughout most layers, the relu activation function is employed, Meanwhile, the output layer employs a function of linear activation. Afterward, the model undergoes compilation through the" model. compile ()" method. At this stage, we define the optimization algorithm commonly used in training neural networks (Adam optimizer), utilize MSE as the loss function, and include RMSE, MSE, and MAE for assessing the model. Subsequently, the model undergoes training using the method of" model . fit()". This involves providing the inputs that include both the training data and target variables that involve 150 epochs. Simultaneously, the model's performance is assessed utilizing the validation data parameter.

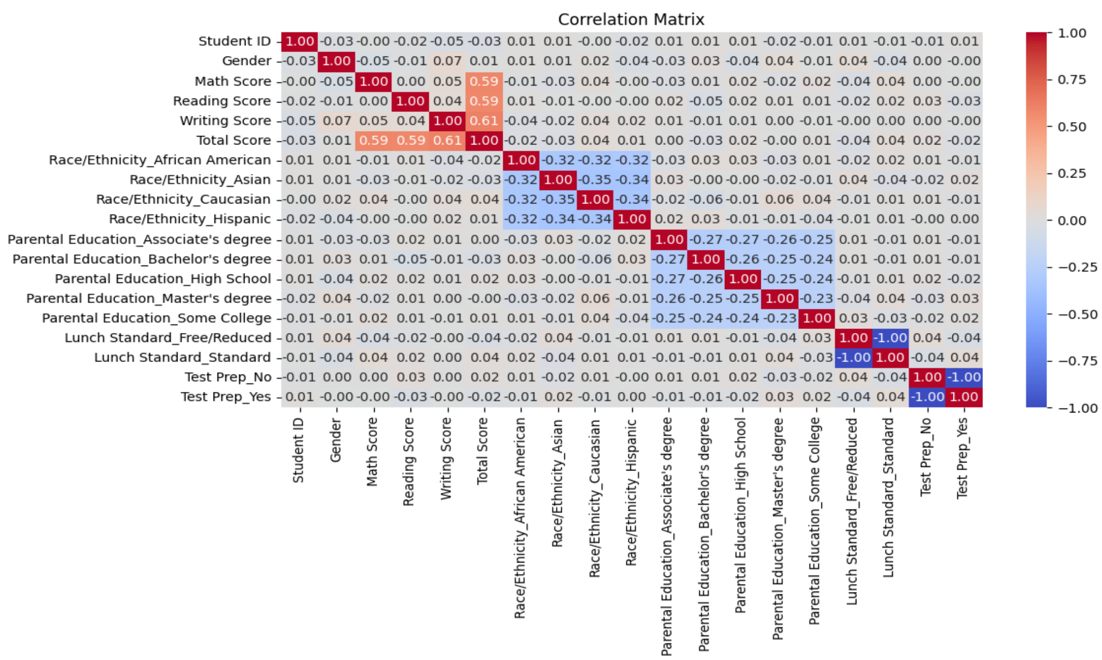


FIGURE 4. **Correlation study results**

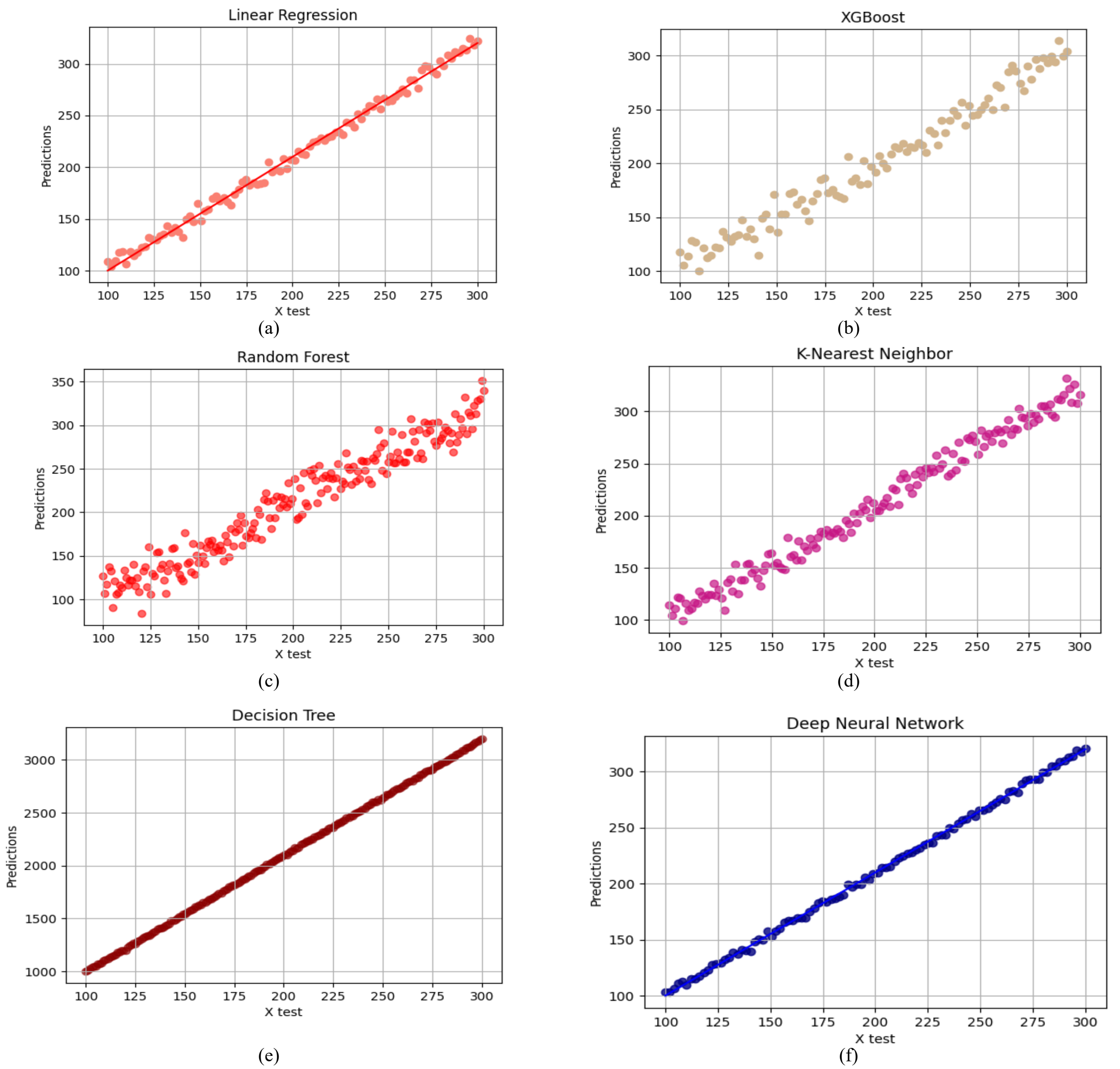


FIGURE 5. This figure represent the prediction of Models: (a) Linear Regression plot, (b) XGBoost plot, (c) Random Forest plot, (d) K-Nearest Neighbors plot,(e) Deep Neural Network plot ,(f) Decision Tree plot

G. Assessing Performance and Outcomes through Regression Plots

In the assessment of ML algorithms, we incorporated plots of regression alongside diverse performance metrics such as MAE, MSE, RMSE and the R-squared score. Regression plots provide a graphical depiction of the relationship between 2 variables, displaying the line representing the predictions of model. This tool aids in evaluating the performance of ML models and discerning data trends and patterns. We specifically utilized plots of regression to visually represent the predictions through testing conducted on the test set (y test), Illustrating the correlation from predicted values, and observed values. These visualizations provided valuable insights into the models' capability to accurately forecast students' total scores, as demonstrated in Figures 7 through 12. In Python, regression plots can be created using the regplot() function from the Seaborn library. After analyzing the regression plots of the employed models, it's evident that the DNN model exhibits a superior fit to the data.

H. Performance Metrics in Machine Learning

Performance metrics in machina learning furnish quantitative measures for assessing the efficacy of models in capturing patterns and making precise predictions. Key metrics such as

R-squared, MAE, MSE, and RMSE provide valuable insights into the degree to which a model fits the data and the proximity of its predictions to actual values [29].

TABLE 6
Evaluation of models using RMSE, R-squared, MSE, and MAE

Model	R-Squared(%)	MAE	MSE	RMSE
k-NN	98.75	1.42	3.49	1.88
DNN	99.96	0.47	0.07	1.16
LR	99.12	3.43	1.85	4.28
DT	97.35	3.19	17.27	4.18
RF	98.63	1.47	4.05	2.03
XGB	96.07	6.05	49.91	7.12

TABLE 7
Comparison of Machine Learning Techniques for Predicting Student Performance

Author	Method	Result	Accuracy
This Study	Deep Neural Network (DNN)	Outstanding performance with an R-squared of 99.96%, MAE of 0.47, MSE of 0.07, RMSE of 1.16	99.96%
This Study	Linear Regression (L.R)	Effective in capturing linear relationships but lower performance on complex data with higher error metrics	99.12%
Yang[7]	BiLSTM with attention mechanism	Achieved significant accuracy in predicting student grades	91.15%
Pelima[4]	Decision Tree	Extensive application in predicting student grades, demonstrated effectiveness	Not specified
Subbarayudu [3]	K-Nearest Neighbor (KNN)	Effective in similarity-based predictions but may struggle with high-dimensional data	Not specified

By scrutinizing these metrics, researchers and practitioners can compare various models, discern their strengths and limitations, and make well-informed decisions regarding model selection and optimization strategies. In this study, a range of performance metrics were employed to assess the effectiveness of the machine learning models. The R-squared score assesses the proportion of the target variable's variance explained by the model, with a higher score indicating a better fit. MAE calculates. The average absolute difference between predicted and actual values, where a lower MAE signifies greater accuracy. Likewise, MSE computes the average squared difference between predicted and actual values, with lower values indicating a better fit. RMSE quantifies the mean error calculated in units consistent with the target variable, with lower values suggesting greater precision. TABLE 6 presents the MAE, RMSE, MSE, R-squared and values for the various ML-models utilized.

V. DISCUSSION

From the regression plots and analyzing the results, it is evident that the Deep Neural Network (DNN) model has emerged as the best performing, showing an outstanding coefficient of determination at 99.96% with minimal error metrics such as Mean Absolute Error (MAE) at 0.47, Mean Squared Error (MSE) at 0.07, and Root Mean Squared Error (RMSE) at 1.16. This performance underlines the robustness of DNN and its ability to model complex nonlinear relationships inherent in the data. The performance of the DNN model in this study is consistent with findings from other research where deep learning models have demonstrated superior capabilities in handling complex datasets with nonlinear relationships. For instance, similar studies (TABLE 7) in educational data mining have reported high accuracy and low error rates with DNN models compared to traditional regression techniques. Linear Regression (L.R) models, while effective in capturing linear relationships, generally fall short in performance when dealing with more complex patterns, as seen in this study where the L.R model had an R-squared of 99.12% but higher error metrics. Despite the impressive results, there are several limitations to consider. The DNN model, while highly accurate, is computationally intensive and may require significant resources for training and deployment. Additionally, the model's performance is highly dependent on the quality and quantity of the data, which may limit its generalizability to other datasets or domains. Furthermore, the simplicity and interpretability of Linear Regression models are often preferred in some applications despite their lower performance in complex datasets. The K-Nearest Neighbors (K-NN) model, though effective in similarity-based predictions, may struggle with high-dimensional data, indicating potential issues with the curse of dimensionality. The findings from this study have several implications for the application of machine learning models in educational data analysis [30]. The superior performance of the DNN model suggests that deep learning techniques can be highly effective in predicting student performance, potentially leading to more accurate and timely interventions. However, the resource requirements and complexity of these models must be carefully managed. The study also highlights the need for a balanced approach, where simpler models like L.R or ensemble methods such as Random Forest (R.F) can be used in conjunction with more complex models to provide comprehensive insights. Future research should explore hybrid models and techniques to leverage the strengths of different approaches while mitigating their weaknesses.

A. Implications for Educational Practices and Policy

This study highlights the significant potential of machine learning models, particularly Deep Neural Networks (DNN), in educational settings. The superior performance of DNN models suggests they could be instrumental in developing advanced predictive tools for identifying at-risk students. Such tools would enable educators and policymakers to implement proactive interventions and provide personalized support tailored to individual student needs. Additionally, the insights gained from these models could inform the development of curricula, allocation of resources, and the creation of supportive education policies that foster an inclusive and effective learning environment for all students. This approach not only enhances student performance but also ensures that educational practices are data-driven and adaptive to the diverse needs of the student population.

B. Future Directions and Limitations

It, however, points out more research that should be conducted but seems promising. The study in the future may look more to integrate variables in terms of behavioral and socio-emotional to understand how they influence the prediction of student performance. Investigation of the applicability of these models across diverse settings and to other levels of education would, of course, open a broader understanding of their utility and scalability. A notable limitation of this study is its reliance on a single dataset. These might improve the generalization of the results if the models are validated in other datasets under different educational contexts. Additionally, DNNs perform better than non-deep learning models, but this 'black box' problem remains, making the model uninterpretable when applying them to specific interventions. Efforts to demystify the decision process of DNNs or create more interpretable models without any significant degradation of performance would add value. The proof of concept through this study is that machine learning models, especially DNN, could efficiently be used for student performance, hence leading the way to the use of technology in gaining efficiency for educational outcomes. Further, refinement in these models and the study of practical applications for them can help us proceed substantially forward in building more personalized and effective systems of education.

VI. CONCLUSION

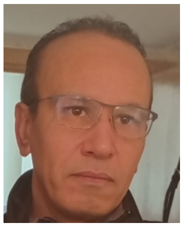
The main aim of this research is to utilize ML algorithms for predicting performance of students. After implementing and assessing various machine learning algorithms, our results indicate that the D.N.N model outperforms other approaches in terms of error metrics and the determination coefficient with 99.96% as determination coefficient and minimal errors, the D.N.N demonstrates remarkable accuracy in forecasting grades of students. The obtained results carry important ramifications for teachers and supervisors seeking to leverage ML to enhance student achievements and promote academic achievement. Through pinpointing the most efficient algorithms for forecasting student grades, we can attain deeper understandings of the factors impacting the performance of student and customize teaching-process and teaching-methodologies and support mechanisms to address individual student requirements. In summary, this study underscores the transformative capacity of ML in reshaping educational practices by delivering personalized and focused assistance to students. Through continued exploration and enhancement of these methodologies, we can further progress endeavors to empower students in realizing their academic aspirations.

REFERENCES

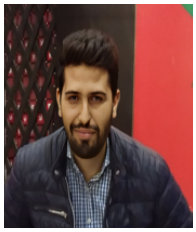
[1] Chen, S., Ding, Y.: A machine learning approach to predicting academic performance in pennsylvania's schools. Social Sciences 12(3), 118 (2023)
[2] Bertolini, R., Finch, S.J., Nehm, R.H.: Quantifying variability in predictions of student performance: Examining the impact of bootstrap resampling in data pipelines. Computers and Education: Artificial Intelligence 3, 100067 (2022)
[3] Subbarayudu, Y., Reddy, G.V., Kumar, M.R., Nai, M.A., Prashanthi, G., Bhalla, L.: Predicting students' failure risk education through machine learning. In: MATEC Web of Conferences, vol. 392, p. 01113 (2024). EDP Sciences.
[4] Pelima, L.R., Sukmana, Y., Rosmansyah, Y.: Predicting university student graduation using academic performance and machine learning: A systematic literature review. IEEE Access (2024).
[5] Kapucu, M.S., O ̈zcan, H., Aypay, A., et al.: Predicting secondary school students' academic performance in science course by machine learning. International Journal of Technology in Education and Science 8(1), 41–62 (2024)
[6] Sandra, L., Lumbangaol, F., Matsuo, T.: Machine learning algorithm to predict student's performance: A systematic literature review. TEM Journal 10(4) (2021)
[7] Yang, X., Zhang, H., Chen, R., Li, S., Zhang, N., Wang, B., Wang, X., et al.: Research on forecasting of student grade based on adaptive k-means and deep neural network. Wireless Communications and Mobile Computing 2022 (2022)
[8] Durak, A., Bulut, V.: Classification and prediction-based machine learning algo- rithms to predict students' low and high programming performance. Computer Applications in Engineering Education 32(1), 22679 (2024)
[9] Rahman, N.H.A., Sulaiman, S.A., Ramli, N.A.: Development of predictive model for students' final grades using machine learning techniques. In: AIP Conference Proceedings, vol. 2895 (2024). AIP Publishing
[10] Novianto, E., Suhirman, S.: Comparison of k-nearest neighbor classification meth- ods and support vector machine in predicting students' study period. Journal of Education & Science 33(1) (2024)
[11] Isnaeni, I.A., Indriani, S., Zaman, M.R.N., Nugroho, A.: Comparison of k-nearest neighbors (knn) and decision tree with binary particle swarm optimization (bpso) in predicting employee performance. International Journal of Open Information Technologies 12(3), 57–65 (2024)
[12] Rimal, Y., Sharma, N., Alsadoon, A.: The accuracy of machine learning models relies on hyperparameter tuning: student result classification using random forest, randomized search, grid search, bayesian, genetic, and optuna algorithms. Multimedia Tools and Applications, 1–16 (2024)
[13] Batool, S., Rashid, J., Nisar, M.W., Kim, J., Kwon, H.-Y., Hussain, A.: Educa- tional data mining to predict students' academic performance: A survey study. Education and Information Technologies 28(1), 905–971 (2023)
[14] Abbas, S., Alsubai, S., Ojo, S., Sampedro, G.A., Almadhor, A., Hejaili, A.A., Bouazzi, I.: An efficient deep recurrent neural network for detection of cyber- attacks in realistic iot environment. The Journal of Supercomputing, 1–19 (2024)
[15] Ashok Kumar, L., Karthika Renuka, D., Naveena, K., Sree Resmi, S.: Crdnn- bilstm knowledge distillation model towards enhancing the automatic speech recognition. SN Computer Science 5(3), 304 (2024)

[16] Kannan, K.R., Abarna, K.M., Vairachilai, S.: Graph neural networks for pre- dicting student performance: A deep learning approach for academic success forecasting. International Journal of Intelligent Systems and Applications in Engineering 12(1s), 228–232 (2024)
[17] Xu, K., Sun, Z.: Predicting academic performance associated with physical fit- ness of primary school students using machine learning methods. Complementary Therapies in Clinical Practice 51, 101736 (2023)
[18] Chen, Y., Zhai, L.: A comparative study on student performance prediction using machine learning. Education and Information Technologies 28(9), 12039–12057 (2023)
[19] A. Bhattacherjee and A. K. Badhan, “Convergence of data analytics, big data, and machine learning: applications, challenges, and future direction,” in Studies in big data, 2024, pp. 317–334.
[20] Bharadwaj, H.K., Agarwal, A., Chamola, V., Lakkaniga, N.R., Hassija, V., Guizani, M., Sikdar, B.: A review on the role of machine learning in enabling iot based healthcare applications. IEEE Access 9, 38859–38890 (2021)
[21] Chaudhary, P.S., Khurana, M.R., Ayalasomayajula, M.: Real-world applications of analytics data, big data, and machine learning. In: Data Analytics and Machine Learning: Navigating the Big Data Landscape, pp. 237–263. Springer, ??? (2024)
[22] Chaitanya, K., Saha, G.C., Saha, H., Acharya, S., Singla, M.: The impact of arti- ficial intelligence and machine learning in digital marketing strategies. European Economic Letters (EEL) 13(3), 982–992 (2023)
[23] Sarkar, C., Das, B., Rawat, V.S., Wahlang, J.B., Nongpiur, A., Tiewsoh, I., Lyn- gdoh, N.M., Das, D., Bidarolli, M., Sony, H.T.: Artificial intelligence and machine learning technology driven modern drug discovery and development. International Journal of Molecular Sciences 24(3), 2026 (2023)
[24] Janiesch, C., Zschech, P., Heinrich, K.: Machine learning and deep learning. Electronic Markets 31(3), 685–695 (2021)
[25] Vovk, Volodya. "Competitive on-line linear regression." Advances in Neural Information Processing Systems 10 (1997).
[26] Qiu, Junfei, et al. "A survey of machine learning for big data processing." EURASIP Journal on Advances in Signal Processing 2016 (2016): 1-16.
[27] Huang, Yongqiang, and Yu Sun. "A dataset of daily interactive manipulation." The International Journal of Robotics Research 38.8 (2019): 879-886.
[28] Suganthalakshmi, T., and M. Saravanakumar. "DATA VISUALIZATION IN THE DIGITAL AGE." PRERANA: Journal of Management Thought & Practice 16.1 (2024).
[29] Erickson, Bradley J., and Felipe Kitamura. "Magician’s corner: 9. Performance metrics for machine learning models." Radiology: Artificial Intelligence 3.3 (2021): e200126.
[30] Yağcı, Mustafa. "Educational data mining: prediction of students' academic performance using machine learning algorithms." Smart Learning Environments 9.1 (2022): 11.

Ahmed Abatal obtained a bachelor's degree in computer science and industrial engineering from the Settat Faculty of Science and Technology (FSTS) in 2011. He then pursued a master's degree in distributed information systems at the École normale supérieure d'enseignement technique de Mohammedia, from which he graduated in 2013. In 2021, he obtained his PhD in computer science from the same institution. His research interests include machine learning, deep learning, healthcare architecture in ubiquitous computing and SQL to SPARQL conversion. Dr. Abatal has contributed extensively to the field, with numerous publications in reputable and indexed scientific journals.



Adil Korchi is an Assistant Professor at the Faculty of Sciences and Economics, Juridical and Social Studies (FSEJS) in El Jadida. He holds a PhD in Informatics and has significant research experience in machine learning, artificial intelligence, and data analytics. Dr. Korchi's work centers on developing innovative approaches that apply machine learning techniques to address complex challenges across various fields. His contributions to these areas are widely recognized, with numerous publications in leading journals and presentations at both national and international conferences, showcasing his impact on the academic and scientific communities.



Mourad Mzili is a researcher in the Department of Mathematics at Chouaib Doukkali University, specializing in optimization and applied mathematics. He earned his Master’s degree in Mathematics from the Faculty of Sciences at Chouaib Doukkali University in El Jadida, Morocco. His research focuses on advancing mathematical methods for optimization, contributing to both theoretical and practical aspects of the field. Mourad Mzili is dedicated to pushing the boundaries of mathematical knowledge, and his work has had a significant impact, reflected in his ongoing research and contributions to the academic community.

Toufik Mzili is a professor and researcher at Chouaib Doukkali University, specializing in optimization and artificial intelligence. He has made substantial contributions to these fields, with an extensive publication record that includes numerous articles in prestigious Q1 and Q2 journals. Dr. Mzili is also highly esteemed for his roles as a seasoned reviewer and editor for respected academic journals. In addition to his editorial work, he has edited multiple indexed books, further solidifying his reputation as a leading expert in his domain. His work continues to influence and advance the fields of optimization and AI.

Hajar Khallouki born in 1989, she completed her Master’s degree in computer science from Faculty of Sciences, Hassan II University, Casablanca, Morocco. In pursuit of a PH.D, she joined the Department of Mathematics and Computer Sciences, Faculty of Sciences and Technology, Hassan I University Settat, Morocco, in 2013. In 2019, she joined Lakehead University Canada as a Postdoctoral Fellow. Her actual main research interests concern multimedia documents adaptation, context awareness, smart cities, and semantic web.

Mohammed El Kaim Billah is a researcher in the Department of Informatics at Chouaib Doukkali University, specializing in Modeling, Applied Mathematics, Data Science, and Statistics. With a robust academic background and extensive expertise in these areas, Dr. El Kaim Billah plays a pivotal role in advancing knowledge within the realm of Applied Sciences. His research focuses on developing innovative methodologies and models that contribute to solving complex problems across various domains. Dr. El Kaim Billah's contributions are highly regarded in the academic community, reflecting his dedication to advancing the fields of modeling and data science.