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Neural Network Model for Predicting Digital Competencies of Teacher Trainers: Insights for Educational Practice

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ABSTRACT

This study explores the application of neural networks for predicting the digital competency levels of teacher trainers. A dataset of 345 trainers, assessed using the DigComp framework, was analysed to identify key digital competencies. Traditional machine learning models often struggle to capture the intricate, non-linear relationships between digital skills. In contrast, neural networks excel in modelling these complexities. Our model, configured with a single hidden layer and ReLU activation (Rectified Linear Unit), achieved strong performance, with an AUC (Area Under the Curve) of 0.901 and a classification accuracy of 75.9%. Key competencies, such as Problem Solving (PS), Digital Content Creation (DCC), and Safety (SAF), emerged as the most influential factors in determining digital mastery. Additionally, interpretability tools were applied to enhance the transparency of the model's predictions, making the results actionable for educators and policymakers. This study demonstrates the potential of neural networks in educational research and competency assessment.

KEYWORDS

Neural network, Digital competencies, Teacher trainers, Educational data mining, DigComp

1. Introduction

In today's rapidly evolving digital landscape, educators, particularly teacher trainers, require a broad range of digital competencies to prepare future teachers for a digitally integrated society. As digital technologies become increasingly embedded in educational systems, these competencies are essential for adapting to new teaching paradigms and fostering interactive learning environments [1]. Frameworks such as the European Digital Competence Framework for Citizens (DigComp) provide structured approaches to assess and develop digital proficiency across domains such as information literacy, digital content creation, and online safety, all critical in modern education [2].

However, predicting digital competency levels is challenging due to the multifaceted nature of digital skills, which encompass technical, pedagogical, and cognitive elements. Traditional models like logistic regression often struggle to capture the intricate, non-linear relationships among these variables, limiting their predictive accuracy [3]. In response to these challenges, deep learning models, particularly neural networks, have emerged as powerful tools for predicting digital competencies. Neural networks excel at modeling non-linear relationships and capturing complex dependencies between variables, providing insights that conventional models may overlook [4].

This study aims to explore the use of neural networks in predicting the digital competency levels of teacher trainers, using the DigComp framework as a foundation. By incorporating interpretability tools, this research seeks to offer actionable insights into the factors influencing digital proficiency, thus advancing the field of educational data mining and providing practical, interpretable results for educators and policymakers.

2. Scope and Methodology

2.1 Dataset Description

The dataset used in this study consists of 345 teacher trainers from various regional centers for education and training in Morocco. The participants come from diverse demographic and professional backgrounds, and their digital competencies were assessed based on the DigComp framework, which is a widely used European framework for measuring digital competencies across various sectors, including education. The data were collected using a questionnaire adapted from the DigComp framework, which allowed for the assessment of multiple dimensions of digital competencies.

The dataset includes the following variables:

Variable Name	Description	Type
Gender	Male or female	Categorical
Years of Experience in Teaching	Less than 10 years and more than 10 years	Categorical
Field of Expertise	Sciences, Languages and Humanities	Categorical
Information and Data Literacy (IDL)	A numerical variable representing the score obtained in this competency	Numerical
Communication and Collaboration (CC)	A numerical variable measuring communication and collaboration competency	Numerical
Digital Content Creation (DCC)	A numerical variable representing digital content creation skills	Numerical
Safety (SAF)	A numerical variable assessing digital safety and data protection	Numerical
Problem Solving (PS)	A numerical variable indicating problem-solving skills in digital environments	Numerical
Level of Mastery of Digital Competencies	A categorical variable divided into four levels: Novice, Basic, Intermediate, and Proficient	Categorical

2.2 Neural Network Model

The neural network model used to predict digital competency levels was configured with the following characteristics:

- Number of hidden layers: the model consists of a single hidden layer. This architecture was selected after testing various configurations (including models with 2 and 3 hidden layers), with this particular setup yielding the best performance in terms of predictive accuracy and efficiency.

- Activation Function: The activation function used for the hidden layer was ReLU (Rectified Linear Unit). ReLU was chosen for its ability to handle non-linearity while avoiding the vanishing gradient problem, making it well-suited for classification tasks.

- Output Layer: The output layer uses the Softmax activation function, which is appropriate for multi-class classification tasks. Softmax outputs probabilities for each class (Novice, Basic, Intermediate, Proficient), facilitating classification.

2.3 Training and Validation

a) Training Process

The 5-fold cross-validation method was used to train the model. The dataset is split into five equal subsets using this method. Four folds are utilized for training while the remaining fold is used for testing in each iteration. To make sure that every fold is utilized for both training and evaluation, this process is performed five times. Cross-validation makes sure that performance is independent of a particular subset of data, which strengthens the model's robustness.

b) Optimization and Loss Function

The Adam optimization algorithm was used to adjust the model's weights. Adam is particularly well-suited for complex models as it combines the benefits of both stochastic gradient descent and adaptive learning rates, helping the model converge more quickly and effectively.

The difference between the actual class labels and the projected probability was measured using the cross-entropy loss function. Since this loss function penalizes inaccurate predictions more severely for underrepresented classes, it is well suited for multi-class classification applications.

c) Regularization

To prevent overfitting, regularization was applied using dropout with a rate of 0.5. Dropout randomly disables 50% of the neurons during training in each iteration, which prevents the model from becoming overly reliant on specific neurons and enhances its ability to generalize to unseen data.

2.4 Model Evaluation

Several exacting indicators were used to examine the model's performance, giving rise to a thorough evaluation of its capabilities. The metrics listed below were applied:

- AUC (Area Under the Curve): This measure was employed to evaluate the discriminating power of the model between the various digital competency levels.

- Classification Accuracy (CA): The proportion of accurate predictions made overall in each class.

- F1-Score: This measure, which is a harmonic mean of recall and precision, offers a fair assessment of the model's effectiveness, especially for underrepresented classes.

- Precision: Indicates the percentage of accurate positive predictions the model makes.

- Recall: Evaluates how well the model can recognize all pertinent instances of the positive class.

- Matthews Correlation Coefficient (MCC): A reliable metric that provides a thorough understanding of the model's performance, particularly in multi-class classification issues, by accounting for true positives, false positives, true negatives, and false negatives.

2.5 Interpretation of Results

To better understand the influence of each variable on the prediction, an analysis of feature importance was conducted using techniques such as the Gain Ratio and the Gini Index. This analysis identified the most impactful digital competencies for predicting the level of mastery of the teacher trainers

3. Related work

3.1 Neural Network Algorithms for Prediction in Education

Because neural networks can accurately predict academic outcomes and model complex interactions between various variables, they are becoming a more and more popular tool in educational data mining. Several studies have applied neural networks in various educational contexts to predict student performance, course selection, and talent identification.

- Predicting Student Performance: One common use of neural networks in educational research is the prediction of students' academic outcomes. For instance, Oancea et al. (2013) [5] employed a multilayer perceptron (MLP) to forecast the grade point average (GPA) of university students based on their background data collected at the time of enrollment. Their model demonstrated significant accuracy in identifying students who were at risk of underperforming academically. In a similar study, Aydoğdu (2019) [6] used neural networks to predict the academic results of university students in an online learning environment, focusing on key factors such as content scores, time spent on learning materials, participation in live sessions, and overall engagement.

- Course Selection and Student Satisfaction: In the context of online education, predicting student satisfaction and course selection is crucial for optimizing resource allocation and course offerings. Kardan et al. (2013) [7] used neural networks to model student course selection behavior in online higher education institutes. The model successfully predicted the number of students who would enroll in specific courses, allowing universities to plan more effectively.

- Predicting Academic Success and Retention: Predicting student success and retention is vital for universities aiming to reduce dropout rates. Rodríguez-Hernández et al. (2021) [8] systematically implemented artificial neural networks to predict students’ academic performance in Colombia, achieving an accuracy of over 80% for high-achieving students. Similarly, Isljamović and Suknović (2014) [9] applied neural networks to predict academic success at the University of Belgrade, identifying key factors that influenced students' final GPA, such as personal and high school data.

- Talent Identification: Neural networks have also been used to predict students’ aptitude in specific areas such as programming. Çetinkaya and Baykan (2020) [10] developed a model to use middle school pupils' success in coding activities to forecast their programming talent. The model achieved high accuracy, demonstrating the potential of neural networks in identifying talent at an early stage.

- Student Performance in Online and Traditional Learning: Baashar et al. (2022) [11] reviewed the use of artificial neural networks to predict academic performance across various learning environments. Their findings indicated that neural networks are highly effective in predicting student outcomes in both traditional and online learning contexts, although more work is needed to apply these techniques in real-world educational settings.

- Evolutionary Neural Networks: Arunachalam and Velmurugan (2018) [12] proposed an evolutionary approach by combining genetic algorithms with neural networks to predict student success more accurately. This hybrid method improved the traditional neural network structure by optimizing the weights assigned to hidden nodes during the learning process.

- Yearly Performance Prediction: Predicting students' performance over a full academic year using neural networks has also been explored. Sikder et al. (2016) [13] applied a neural network to predict students' cumulative GPA at Bangabandhu Sheikh Mujibur Rahman Science and Technology University, achieving high accuracy in forecasting yearly performance .

- Early Dropout Prediction: Albarka (2019) [14] used neural networks to predict the likelihood of students dropping out or experiencing delays in graduation at Katsina State Institute of Technology and Management. By identifying at-risk students early, the institution was able to design intervention programs to improve retention rates.

These studies demonstrate that neural networks are a versatile and effective tool for predicting a wide range of academic outcomes, from course selection and GPA to identifying at-risk students and programming talent. Despite their success, challenges remain, particularly in applying these models in real-world educational environments and improving their interpretability for non-technical stakeholders.

3.2 Prediction of Digital Skills of Teacher Trainers

The prediction of digital competencies, particularly among teacher trainers and higher education instructors, has become increasingly relevant as the integration of digital tools in educational settings has accelerated, especially following the COVID-19 pandemic. While many studies have focused on students' digital skills, recent research has started to explore how to assess and predict the digital competencies of educators using advanced machine learning techniques.

- Classification Models Based on the DigCompEdu Framework: In a study conducted by Cabero-Almenara et al. (2021) [15], machine learning methods, including logistic regression and classification trees, were employed to predict the digital competence levels of higher education teachers using the DigCompEdu framework. This framework, developed by the European Commission, provides a detailed assessment of digital skills across six key areas. The study, which included 1,104 higher education teachers from Andalusia, Spain, found that logistic regression achieved a higher success rate (83.7%) in classifying digital competencies compared to the classification tree method (81.7%). The analysis revealed that factors such as the time spent creating digital content and using advanced technologies like virtual reality and gamification were strong predictors of high digital competence in areas such as the creation and use of digital resources. This study highlights the importance of specific digital teaching practices in developing digital skills at a leader or expert level among educators.

- Machine Learning for Digital Competency Assessment: Similarly, Yang (2023) [16] explored the use of machine learning to assess the digital competencies of university instructors. In contrast to traditional self-assessment methods, which are prone to bias, this study utilized machine learning algorithms to analyze syllabi and measure the extent to which digital competencies were integrated into course design. The study's results showed that machine learning-based assessments were highly consistent with human evaluations, proving the feasibility of using AI to assess digital competencies objectively and efficiently.

Yang's research contributes to the growing body of literature on how machine learning can be applied to automate the assessment of digital skills among educators. The methodology employed in this study provides higher education institutions with a scalable and efficient tool for monitoring the digital competence of their faculty. As digital tools and remote learning continue to be an essential part of modern education, such methods are crucial for ensuring that educators remain equipped to handle new technological challenges.

These studies underscore the potential of machine learning techniques, including neural networks, in predicting digital skills among educators. However, the field remains underexplored compared to student-focused research. More studies are needed to further validate these models and assess their applicability in diverse educational contexts. As machine learning models become more sophisticated, their integration into teacher training programs offers a promising path for improving digital competencies in education.

4. Result and finding

4.1 Performance Metrics of the Neural Network Model

The performance of the neural network model was evaluated using several rigorous metrics to provide a comprehensive view of its accuracy and robustness in predicting the levels of digital competency. The results demonstrate that the model performed well across all key metrics, indicating its effectiveness in capturing the complexity of the data. Table 1 presents the detailed performance metrics of the neural network model.

Table 1 Performance Metrics of the Neural Network Model

Metric	Score
AUC (Area Under the Curve)	0.901
Classification Accuracy (CA)	0.759
F1-Score	0.758
Precision	0.76
Recall	0.759
MCC (Matthews Correlation Coefficient)	0.671

- AUC (Area Under the Curve): The AUC of 0.901 indicates that the model has excellent discriminative power across the four classes of digital competency. An AUC above 0.9 signifies that the model can clearly distinguish between different levels of competency, a critical factor in this multi-class classification task.

- Classification Accuracy (CA): The model achieved a classification accuracy of 75.9%, meaning it correctly predicted the digital competency level for approximately 76% of the teacher trainers. This reflects strong overall performance across the dataset.

- F1-Score: The model, especially for less-represented classes, effectively minimizes both false positives and false negatives by maintaining a balanced trade-off between precision and recall, with an F1-score of 0.758.

- Precision and Recall: The precision of 0.760 and recall of 0.759 further support the model’s strong predictive ability, showing it can correctly identify relevant cases while minimizing incorrect classifications.

- MCC (Matthews Correlation Coefficient): An MCC of 0.671 reflects a good correlation between the predicted and actual outcomes, taking into account true and false positives and negatives. This metric is particularly useful in assessing the model’s performance in multi-class classification scenarios like this one.

4.2 Confusion Matrix Analysis

To further understand the model’s performance in classifying individual competency levels, a confusion matrix was generated, highlighting where the model made correct predictions and where it struggled. The matrix provides a detailed breakdown of classification errors, particularly between classes with adjacent competency levels.

Table 2 Confusion matrix analysis

Actual Class	Predicted Class	Correct	Misclassified as Novice	Misclassified as Basic	Misclassified as Intermediate	Misclassified as Proficient
Novice	Novice (36/52)	36	-	15	1	-
Basic	Basic (87/104)	87	10	-	6	1
Intermediate	Intermediate (81/113)	81	2	16	-	14
Proficient	Proficient (58/76)	58	-	1	17	-

Key observations:

- Novice Class: 36 out of 52 "Novice" instances were correctly classified, with 15 being misclassified as "Basic." This suggests that the model has difficulty distinguishing between "Novice" and "Basic," likely due to the similarity in their digital competency profiles.

- Basic Class: The model classified 87 out of 104 "Basic" instances correctly, with minor errors, mostly confusing "Basic" with the adjacent classes "Novice" and "Intermediate."

- Intermediate Class: The "Intermediate" class was more challenging for the model, with 81 out of 113 correctly predicted. There were 16 misclassifications as "Basic" and 14 as "Proficient," indicating that the model struggles to differentiate intermediate competencies from the neighboring classes.

- Proficient Class: For the "Proficient" class, 58 out of 76 were correctly classified. However, 17 instances were incorrectly classified as "Intermediate," showing a slight overlap in distinguishing the highest competency levels.

4.3 Receiver Operating Characteristic (ROC) Curves

The ROC curves provide a visual representation of the model's discriminative ability for each class. The AUC scores for each class are indicative of how well the model distinguishes that class from others.

- Novice: AUC near 1.0, showing excellent separation between "Novice" and other competency levels (Fig. 2).

- Basic: Similarly high AUC, reflecting strong performance in distinguishing "Basic" from the other categories (Fig. 2).

- Intermediate: The model faced more difficulties here, as reflected by minor fluctuations in the ROC curve, yet the AUC remains high overall (Fig. 2).

- Proficient: While performance was slightly lower than the "Basic" and "Novice" classes, the model still shows good separation for "Proficient," with an AUC significantly above random classification (Fig. 2).

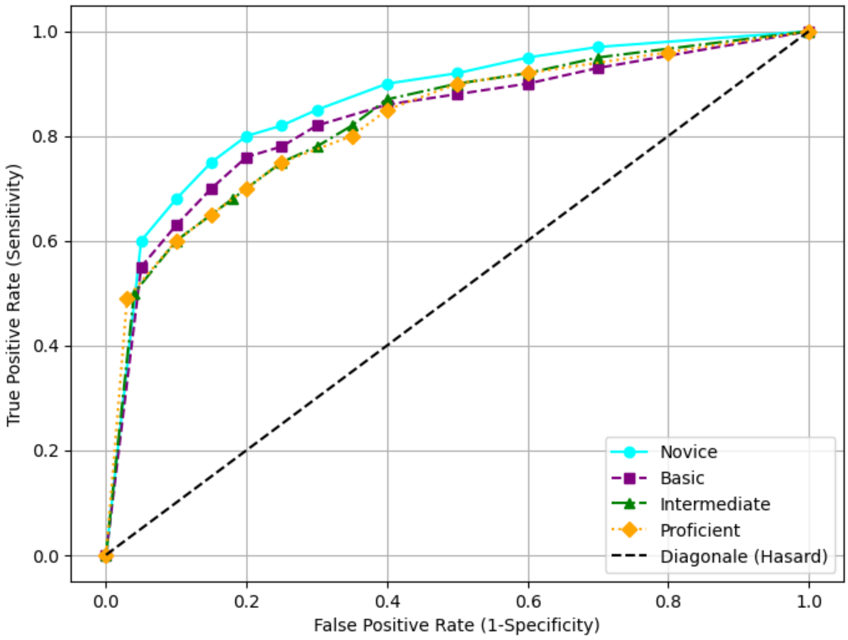

Figure 1 ROC curves

4.4 Feature Importance Analysis

The analysis of feature importance provides insights into which digital competencies most significantly influenced the model's predictions. The Gain Ratio and Gini Index were used to assess the contribution of each competence.

Competency	Gain Ratio	Gini Index
Problem Solving (PS)	0.350	0.223
Digital Content Creation (DCC)	0.302	0.199
Safety (SAF)	0.285	0.169
Communication (CC)	0.241	0.138
Information Literacy (IDL)	0.220	0.127

- Problem Solving (PS) emerged as the most influential competency, with the highest Gain Ratio (0.350). This aligns with expectations, as problem-solving skills are often a key indicator of overall digital competency.

- Digital Content Creation (DCC) and Safety (SAF) also had high importance, reflecting the need for technical skills and security awareness in digital environments.

- Communication (CC) and Information Literacy (IDL), while still influential, were less critical compared to the others. This might suggest that these competencies, though essential, may be more foundational and widespread, hence contributing less to the classification between different levels of mastery.

5. Discussion and Conclusion

This study highlights the potential of neural networks in predicting the digital competencies of teacher trainers. Achieving an AUC of 0.901 and a classification accuracy of 75.9%, the model effectively captured intricate, non-linear relationships between digital competency factors. Problem-solving (PS) emerged as the most critical predictor, alongside Digital Content Creation (DCC) and Safety (SAF), emphasizing their importance in modern teacher training programs. Despite the strong performance, challenges such as misclassifications between adjacent competency levels (e.g., Novice vs. Basic, Intermediate vs. Proficient) revealed the model's difficulty in differentiating closely related levels, likely due to overlapping features.

The practical implications underscore the need for teacher training programs to prioritize problem-solving and digital content creation, alongside promoting digital safety awareness. These focus areas are vital for equipping trainers to effectively utilize and teach digital tools in secure, efficient ways. Furthermore, this research demonstrates the viability of automated systems based on neural networks for personalized assessments, enabling data-driven recommendations tailored to individual needs.

However, limitations remain. The relatively small dataset of 345 participants, restricted to Moroccan teacher trainers, limits the generalizability of the findings. The class imbalance also impacted the accurate prediction of less-represented levels, such as Proficient. Additionally, neural networks' "black-box" nature continues to pose interpretability challenges, which is crucial for educational stakeholders.

Future research should focus on expanding datasets to include more diverse populations and employing techniques like SMOTE to address class imbalance. Advanced neural models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) could capture dynamic aspects of competency development. Longitudinal studies could further explore how digital competencies evolve over time and how neural networks can provide ongoing feedback to educators. Moreover, adopting interpretability tools like SHAP or LIME would make neural network predictions more transparent and actionable.

In conclusion, neural networks offer a robust approach for digital competency assessment, enabling scalable, precise, and adaptive solutions for teacher training programs. By addressing existing limitations and exploring advanced methodologies, these models hold great promise for enhancing professional development and fostering digitally competent educators.

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