International journal of applied management and economics
Vol : 02 , N° 10 , October 2024
ISSN : 2509-0720

Using Artificial Intelligence and Deep Learning for Predictive Modeling in Regional Development.

– **Author 1 :** Asmaa FARIS,
– **Author 2 :** Mostafa ELHACHLOUFI,

(1) : PhD Student, Faculty of Legal, Economic, and Social Sciences Ain-Sbaa, University Hassan II, Casablanca, Morocco.
(2) : Doctor, Faculty of Legal, Economic, and Social Sciences Ain-Sbaa, University Hassan II, Casablanca, Morocco.

Conflict of interest: The author reports no conflict of interest.

To quote this article: FARIS .A & ELHACHLOUFI .M (2024) « Using Artificial Intelligence and Deep Learning for Predictive Modeling in Regional Development»,
IJAME : Volume 02, N° 10 | Pp: 229 – 257.

Submission date : September 2024
Publication date : October 2024

DOI : 10.5281/zenodo.13928164

ABSTRACT

This study explores the application of artificial intelligence and deep learning, particularly deep neural networks (DNNs), in predictive modeling for regional development. The research uses a dataset of development conventions from the Tanger-Tétouan-Al Hoceïma region in Morocco to forecast the success or failure of these initiatives. Utilizing advanced data mining and deep learning techniques, the study achieves a perfect regression value (R=1), indicating high accuracy in predictions. The results underscore the potential of AI to enhance decision-making processes in regional development while emphasizing the need for meticulous model design and parameter optimization. The study also identifies challenges such as data collection limitations and the presence of outliers. Future research will focus on incorporating qualitative data, expanding the geographical scope, and exploring additional machine learning methods to further refine predictive accuracy and support sustainable regional growth.

KEYWORDS: Artificial Intelligence, Deep Learning, Deep Neural Networks, Regional Development, Predictive Modeling.

1 Introduction

The challenges of regional development are becoming increasingly complex as societies evolve and socio-economic demands diversify. In this context, development conventions, which are formal agreements aimed at promoting growth and cohesion in specific regions, play a crucial role. However, their effective implementation faces numerous obstacles, such as the diversity of stakeholders, the variability of regional contexts, and the constantly changing socio-economic dynamics. Addressing these challenges requires innovative approaches capable of providing precise analyses and reliable forecasts to support decision-making.

Artificial intelligence (AI) and deep learning have emerged as powerful tools to tackle these challenges. In particular, deep neural networks (DNNs) offer exceptional capabilities for modeling complex and nonlinear relationships from large and heterogeneous datasets. The application of these technologies in regional development is still relatively new, but it already shows significant potential for enhancing the understanding of factors influencing the success of development conventions and for predicting their effectiveness.

The objective of this article is to demonstrate how the use of artificial intelligence and deep learning can transform predictive modeling in the field of regional development. These technologies not only allow for the processing and analysis of complex datasets with increased accuracy but also generate insights that can guide public policies and development strategies more effectively.

The paper is structured as follows: it begins with a literature review that examines the theoretical and technical foundations of deep learning, focusing on the most commonly used types of neural networks, such as deep neural networks (DNNs), feed-forward networks, and convolutional neural networks (CNNs). This section also explores the growing application of these techniques in the field of regional development, highlighting their ability to provide innovative solutions to traditional challenges.

Next, the methodology section describes the process of data collection and processing, as well as the methods employed to develop the predictive models. The study focuses on analyzing a dataset specific to development conventions, using data mining tools and neural network models to predict the outcomes of these conventions.

The results of this study, presented in the following section, demonstrate how deep learning models can be used to accurately predict the success or failure of development conventions. The ensuing discussion explores the implications of these results for regional development, highlighting the strengths and limitations of current approaches.

Finally, the article concludes with a summary of the main findings, discusses the limitations encountered during the research, and proposes perspectives for future studies. These perspectives include improving current models by integrating qualitative data, applying the models to a broader range of regional contexts, and exploring new machine learning techniques to further enrich predictive analysis.

In summary, this article aims to show how integrating artificial intelligence and deep learning into predictive modeling can offer innovative solutions to improve the planning and implementation of regional development strategies. These technologies, despite their challenges, present unique opportunities to support sustainable and balanced regional growth.

2 Literature Review

2.1 Deep Learning

Deep Learning, a subcategory of Machine Learning, is characterized by its independence from structured data. This system is based on multiple layers of a "neural network," integrating various algorithms and drawing inspiration from the functioning of the human brain. This approach is particularly useful for complex tasks where all aspects of the objects to be processed cannot be pre-categorized. Notably, the system does not require explicit training by a developer **(IONOS, 2021)**.

Although the concept of deep learning was introduced over 20 years ago, its practical application began in earnest in the 1980s. However, it wasn't until 1995 that these techniques could be practically implemented, likely due to hardware advancements consistent with Moore's Law, as well as conceptual breakthroughs. Significant contributions were made by Alexander Waibel in 1989 **(WAIBEL, 1989)**, Yann LeCun in 1985 **(LE CUN Y. B., 1998)** **(LE CUN Y. , 1985)**, and Geoffrey Hinton, particularly from 1986 onwards **(ACKLEY, 1985)** **(RUMELHART, 1986)**.

2.2 Deep Neural Networks (DNNs)

Starting in 2012, neural networks experienced significant growth, initially emerging in the field of machine learning and subsequently evolving into deep learning. Deep learning is characterized by the use of neural networks with a large number of layers.

The perceptron algorithm, developed by Frank Rosenblatt in 1957, represents a method of supervised learning. The perceptron, also known as a formal neuron in its simplest form, aims to separate observations into two distinct classes, provided that these data are linearly separable. Its primary objective is thus classification.

Communication between neurons occurs through the exchange of messages in the form of variations in action potential. A neuron can receive multiple messages from other neurons to which it is connected.

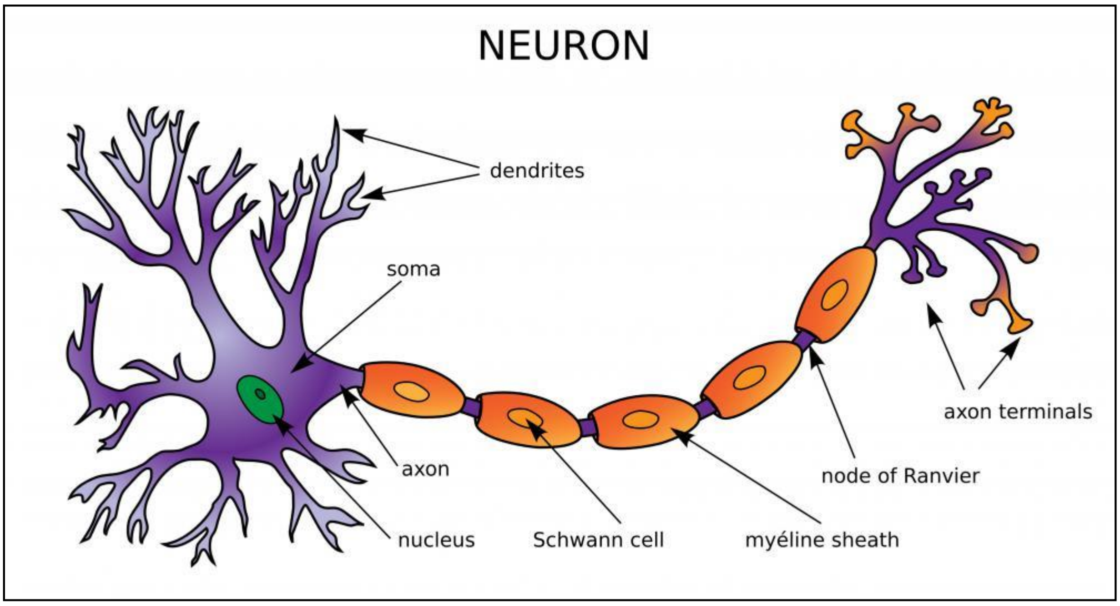

Fig 1. Representation of a Neuron (Source : Quasar Jarosz, quasarj.com)

A neuron receives inputs and generates an output using various characteristics **(RUSSELL, 2010) (MCCULLOCH, 1943)**:

- Weights assigned to each input, modifying the relative importance of certain inputs compared to others.
- An aggregation function, which computes a single value from the inputs and their respective weights.
- A threshold (or bias), indicating when the neuron should activate.
- An activation function, associating each aggregated value with a unique output depending on the threshold.

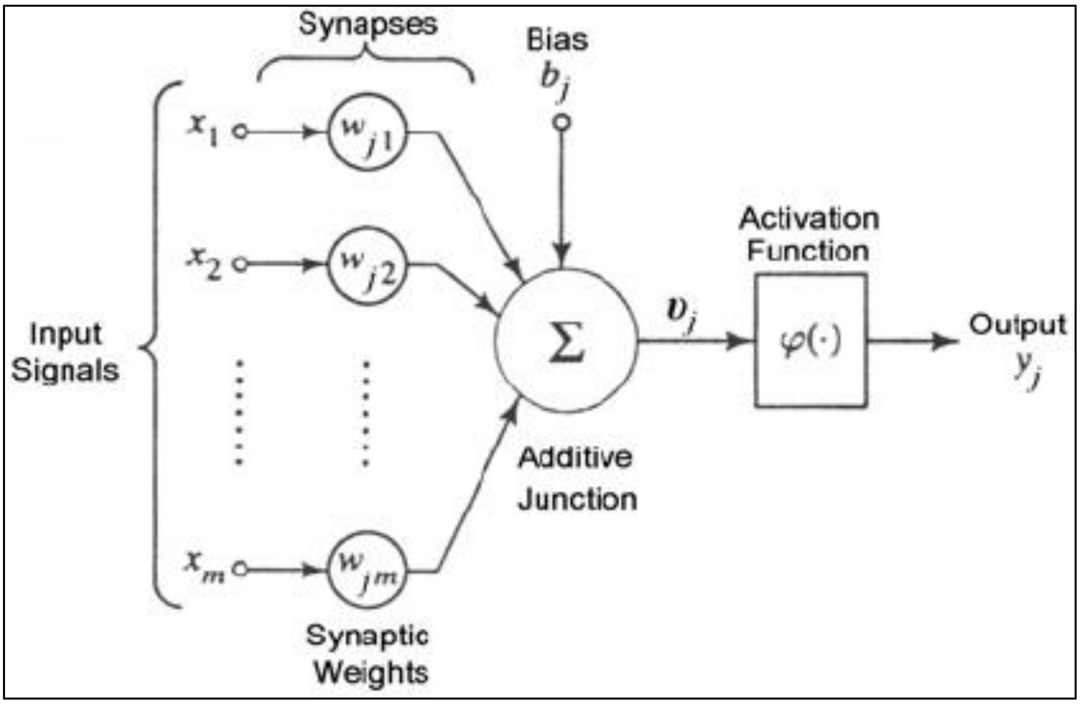

Fig 2. Principle of Neural Network Operation

In the context of multilayer networks, neurons are divided into three distinct categories (CORNUÉJOLS, 2018):

- **Input Neurons**: These units are responsible for transmitting the components of the data vector x, representing the training data during the learning phase.
- **Output Neurons**: These units provide the learning hypothesis.
- **Hidden Neurons**: These units are neither input nor output units. They perform intermediate processing.

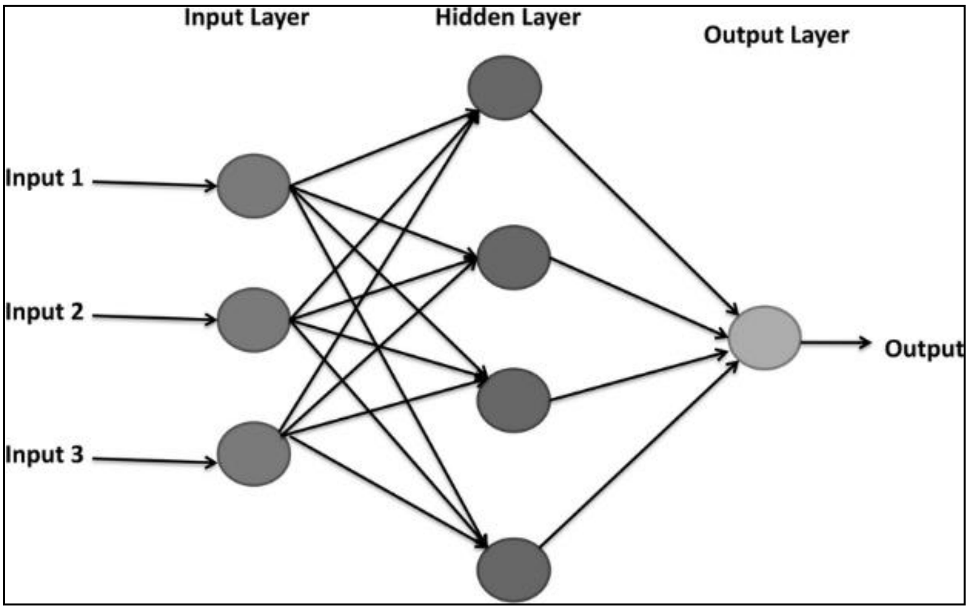

Fig 3. Single-layer neural network

Other models exist, such as the Boltzmann machine, where all formal neurons, regardless of their category, are interconnected (ACKLEY, 1985).

2.2.1 Feed-Foward Networks

Feed-Forward networks, also known as layered networks, overcome the limitations of perceptrons by addressing problems that are not linearly separable. Networks with hidden layers consist of one or more layers of hidden neurons, connected to the inputs or previous layers, and an output layer linked to the hidden neurons. They are referred to as Feed-Forward because information flows only from inputs to outputs, without feedback (RUMELHART, 1986) (BISHOP, 1995) (LE CUN Y. B., 1998).

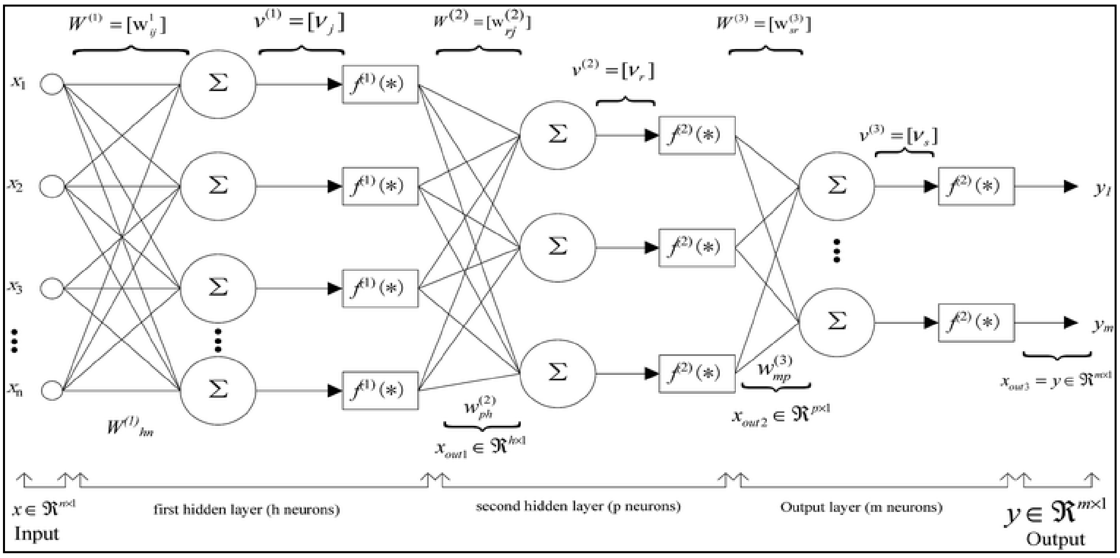

Fig 4. A neural network model with multiple hidden layers

In the context of feed-forward networks, gradient descent with backpropagation is possible, representing an extension of the gradient descent algorithm. The principle of backpropagation involves first adjusting the weights between the output neurons and the hidden neurons, and then propagating the error backward to correct the weights between the hidden neurons and the inputs. This correction is performed example by example, and multiple iterations, ideally with different orders, are required to converge to an optimum (DRIANCOURT, 1994) (LE CUN Y. B., 1998) (BISHOP, 1995).

Although feed-forward networks are widely used, they are not the only category of networks, and there are various architectures suited to different types of problems.

2.2.2 Convolutional Neural Networks (CNNs)

These networks consist of multiple layers, each with distinct roles. For example, convolutional layers process specific parts of an image, acting as feature extractors. Pooling layers combine the outputs of convolutional layers to detect higher-level features, while classification layers, often activated by the ReLU function, perform more traditional classification tasks (HINTON G. E.-W., 2006) (LE CUN Y. B., 1998) (BOSER, 1991).

A non-linear corrective processing is applied between each layer to enhance the relevance of the result. The outputs of one layer form an "intermediate feature map," which serves as the input for the subsequent layer (LE CUN Y. B., 1998) (HINTON G. E., 2012).

These networks are often challenging to train from scratch. Typically, a pre-trained network is used, and specific training is performed on our dataset for a few epochs. This approach, known as transfer learning, allows for achieving classification accuracy greater than 95% with relatively short training times.

2.3 Application of Deep Learning in Regional Development

Deep learning finds prolific application in various aspects of regional development, including urban planning, natural resource management, economic forecasting, and other key areas.

Deep learning plays a crucial role in modern urban planning by helping planners make decisions based on precise and up-to-date data. Convolutional Neural Networks (CNNs) are particularly effective in analyzing satellite images and geospatial data, allowing for highly accurate mapping of urban areas. For instance, a study by (Zhang, 2019) used CNNs to detect changes in urban land use, facilitating more efficient planning and management of urban infrastructure. Additionally, deep learning models can predict areas at risk of urban congestion and propose traffic optimization solutions (H. Huang, 2020). This is especially important in large metropolitan areas where effective traffic management can significantly impact the quality of life for residents.

Deep learning has transformed natural resource management by enabling continuous and precise monitoring of ecosystems. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are commonly used to analyze time series data and predict climatic phenomena. For example, (N. Kussul, 2017) demonstrated how RNNs can be used to forecast agricultural yields based on climate data and satellite images. Additionally, deep learning is employed to monitor forests, detect illegal deforestation, and prevent wildfires through real-time analysis of satellite images. These technologies enable more sustainable management of natural resources and help preserve ecosystems for future generations.

In the economic domain, deep learning offers powerful tools for modeling and forecasting regional economic dynamics. Deep learning models can analyze large amounts of economic data, such as market indicators, consumption trends, and government policies, to predict economic growth and detect market trends. For example, (S. P. Chatzis, 2018) used neural networks to forecast economic crises and propose suitable economic policies. Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) are also employed to generate synthetic economic data, enabling more in-depth analysis of complex economic dynamics (Kingma & Welling, 2014).

Deep learning also contributes to the management of regional infrastructure, including transportation networks, water supply systems, and power grids. Deep learning models can predict failures and optimize maintenance operations. For example, CNN models can be used to analyze images of infrastructure and detect anomalies that may indicate maintenance needs (I. Goodfellow, 2016).This approach helps reduce maintenance costs and improve infrastructure reliability.

In public health, deep learning aids in analyzing epidemiological data and predicting epidemics. Recurrent Neural Networks (RNNs) and LSTM models are used to analyze time series of public health data and forecast infectious disease outbreaks (X. Shi, 2015). Additionally, deep learning models can analyze data from health sensors to predict local epidemics, allowing for quicker and more effective responses from health authorities.

Deep learning is emerging as a powerful tool for regional development, offering innovative and precise solutions across various domains. Its potential to transform urban planning, natural resource management, economic forecasting, infrastructure management, and public health is immense. However, to maximize its effectiveness, it is crucial to continue improving models and overcoming challenges related to data and system complexity. Future research and developments in this field promise to make significant contributions to sustainable and inclusive regional development.

A pioneering study by (A. K. M. Mahbubur Rahman, 2021) utilized deep learning models like FCN-8, U-Net, and DeepLabv3+ to classify urban spaces in cities such as Cairo, Dhaka, and Nairobi. By analyzing satellite images, the study identified formal and informal zones based on socioeconomic criteria. This approach is particularly beneficial for developing cities, where demographic growth and urban sprawl require powerful tools for efficient urban planning. The results demonstrated that the DeepLabv3+ model achieved high accuracy, making it ideal for sustainable urban planning and land-use forecasting.

In a related vein (Chenhui Ding, 2021) explored how the digital economy, bolstered by deep learning technologies, fosters technological innovation and high-quality regional development in developing countries. Their study revealed that digital infrastructure plays a mediating role in regional growth, where deep learning models can enhance spatial and economic data analysis to support strategic decision-making. This connects directly to the findings of Sarker et al. (2021), as these digital tools also facilitate more efficient management of urban resources and infrastructure.

(Ji Luo, 2022) illustrated another application of deep learning in developing regions by analyzing the impact of transportation infrastructure on conflict resolution. Using neural networks, the study provided insights into how infrastructure influences regional stability and economic growth. This complements previous research by emphasizing the importance of integrating both physical and digital infrastructures in regional planning to foster economic growth and social stability.

Lastly, a recent study conducted by (Asmaa Faris, 2024) focuses on the Tanger-Tetouan-Al Hoceïma region and aims to identify the most effective algorithm for modeling the outcomes of development conventions in this strategically important area. This region, known for its economic and social dynamism, serves as an ideal case study for applying advanced techniques in Artificial Intelligence and Machine Learning.

The researchers meticulously explored various algorithms, including decision trees, and ensemble methods, to determine which one would provide the most accurate and reliable predictions. They also considered local specifics, such as economic variations, available infrastructure, and social initiatives, to tailor the models accordingly.

This study highlights the growing significance of Artificial Intelligence in strategic decision-making, particularly in the context of development conventions. The findings not only open up new avenues for improving development policies in the region but also reinforce the relevance of AI as an indispensable tool for planners and decision-makers. By modeling the outcomes of these conventions, the researchers contribute to a better understanding of regional dynamics and propose concrete solutions to maximize the positive impacts of development projects.

Thus, this research marks a turning point in the use of advanced technologies for regional development, while also calling for further studies to refine and optimize the approaches used. By opening up new avenues for research in this field, the results of this study highlighted the potential of deep learning to further enhance the modeling of development convention outcomes. It is in this context that the idea for the current article emerged. Building on the foundations laid by this research, we sought to delve deeper into the application of deep learning, exploring more sophisticated neural network architectures and both supervised and unsupervised learning techniques to refine predictions and better understand the complex dynamics at play in regional development processes. This innovative approach not only enriches the field of applied artificial intelligence but also promises to provide more robust decision-making tools for development stakeholders.

3 Methods

In the context of this study, we endeavored to collect over 310 regional development conventions from the regional council. These conventions were launched in the Tanger-Tétouan-Al Hoceïma region between the years 2016 and 2020. This initiative reflects the active engagement of 146 local governments, each responsible for implementing a distinct set of development projects.

However, the sheer quantity of these conventions in a specific geographical area poses a significant challenge in terms of data collection. Given that Morocco is divided into 12 different regions, each with its unique administrative arrangement, this diversity adds an additional level of complexity to the task of data collection across these 12 regions.

With this in mind, we made the decision to specifically focus on examining the development conventions emanating from the Tanger-Tétouan-Al Hoceïma Regional Council (TTAH). This approach was adopted with the aim of effectively addressing our research objectives and thoroughly analyzing the development initiatives specific to this region.

The Regional Council of TTAH holds conventions with its partners in order to form DCs. Two organizational operational processes were found following a thorough examination of the DCs and conversations with key players in the creation and execution process. Conventions are developed in the first process, and DCs are implemented through procurement contracts in the second process. A DC's ability to succeed depends on the results of conventions. Therefore, in order to perform predictive studies and precisely foresee the outcomes of the DC, it is required to combine the data from conventions and DCs. A deep learning model with a categorical target variable**Y** that indicates "FAIL" or "SUCCESS" is needed for this. Instead of resolving the main issues, the models depend on plans removed from obvious datasets and give experiences to assist the relationship with arriving at better conclusions about how to address business troubles. Here, we utilize a dataset of conventions extracted from an Excel file to conduct a detailed analysis of the convention proposals and determine which ones are successful and which ones are not.

Here, the research variables have been listed.

Table 1. Research Variables

Variable's Notation	Variable's Name	Type
X1	Province	Input
X2	specialization_reg	Input
X3	Sector	Input
X4	cont_reg	Input
X5	cont_partenaires	Input
X6	VISA	Input
X7	delay_partenaires	Input
X8	delay_reg	Input
X9	Type_Territ	Input
X10	Progress	Input
Y	Completion	Target

Source : The Regional Council of TTAH, produced by the authors

The variables chosen for this study are particularly relevant in the Moroccan context, specifically for the Tanger-Tétouan-Al Hoceïma (TTAH) region, for several reasons:

Geopolitical Diversity (**X1** - Province): Morocco's regional diversity, with each region facing unique development challenges and governance structures, makes the inclusion of the province variable crucial. The province captures regional-specific influences on the success or failure of development projects, accounting for differences in local governance, economic conditions, and geographic characteristics.

Specialization of the Region (**X2** - specialization_reg): Different regions in Morocco have varying socio-economic priorities (e.g., agriculture, tourism, industry). This variable reflects the region's strategic focus and how it aligns with national and regional development plans, offering insight into how well conventions address local needs.

Sectoral Focus (**X3** - Sector): Morocco's economy is driven by key sectors like agriculture, tourism, and manufacturing. By including the sector as a variable, the study evaluates how the nature of the sector impacts the likelihood of project success, helping identify which sectors are most conducive to achieving the goals of development conventions.

Contractual Aspects (**X4** - cont_reg, **X5** - cont_partenaires): Successful implementation of development conventions often hinges on strong partnerships. These variables capture the commitments and responsibilities between regional councils and their partners (public or private), highlighting the importance of multi-stakeholder collaboration in development projects.

VISA (**X6** - VISA): In the Moroccan context, "VISA" typically refers to administrative approvals required for projects. The inclusion of this variable emphasizes how bureaucratic processes, regulatory compliance, and the ease of obtaining necessary permits influence project success.

Delays (**X7** - delay_partenaires, **X8** - delay_reg): Delays in the execution of projects, whether caused by the partners or regional authorities, are a significant challenge in Morocco. These variables address the impact of project timelines on completion, an issue particularly relevant in regions where bureaucratic and logistical challenges often lead to prolonged timelines.

Territorial Type (**X9** - Type_Territ): Morocco's regions include urban, rural, and peri-urban areas, each facing distinct development needs. The variable "Type_Territ" accounts for the nature of the territory where a convention is executed, providing insight into whether urban or rural areas are more prone to success or failure.

Project Progress (**X10** - Progress): This variable tracks the ongoing status of projects, which helps monitor the effectiveness of implementation strategies, ensuring that the resources and efforts are aligned with the goals of the conventions.

4 Results and Discussion

4.1 Data mining model

Data mining is a relatively young scientific discipline that enables the discovery of hidden patterns within large datasets. With the exponential growth of data worldwide, its significance has increased substantially, rendering traditional management methods inadequate for big data analysis. Consequently, data mining has become a powerful tool for prediction, classification, clustering, and approximation. Furthermore, it provides a means to solve complex problems by developing appropriate models. Regional development also faces similar challenges, where effective data analysis can help reduce the waste of financial and human resources. It is within this context that we present the following considerations.

4.2 Prediction Completion convention by Deep Neural Network

Data collection is a key step for obtaining concrete and up-to-date information on the implementation of conventions. This phase includes gathering data from official documents, reports, and regional statistics.

This step provides a solid foundation for a thorough analysis of the challenges and opportunities associated with the implementation of conventions. It allows for the development of practical recommendations to improve implementation processes and promote balanced and sustainable regional development.

The dataset underwent rigorous processing using data mining tools, which effectively corrected all outliers and missing elements. Regarding missing values, several instances were identified and addressed during the analysis, thereby ensuring the integrity of the data. Initially, our dataset comprised 310 conventions. However, following an extensive processing phase conducted in Excel, we refined the dataset to obtain a subset containing complete information for 170 conventions.

It is important to note that during the data collection phase, we encountered certain limitations that hindered the acquisition of all the necessary information for each convention. Although these limitations were unfortunate, they were accounted for in the subsequent analysis to minimize their impact on the final results.

Subsequently, we imported the dataset into Matlab Online for advanced analysis. We employed a multi-layer perceptron neural network, featuring an architecture with 10 neurons in the hidden layer. This model was selected for its ability to capture non-linear relationships within the data. The implementation of this network enabled the development of a robust structural model, the configuration of which is illustrated in **Fig 6**.

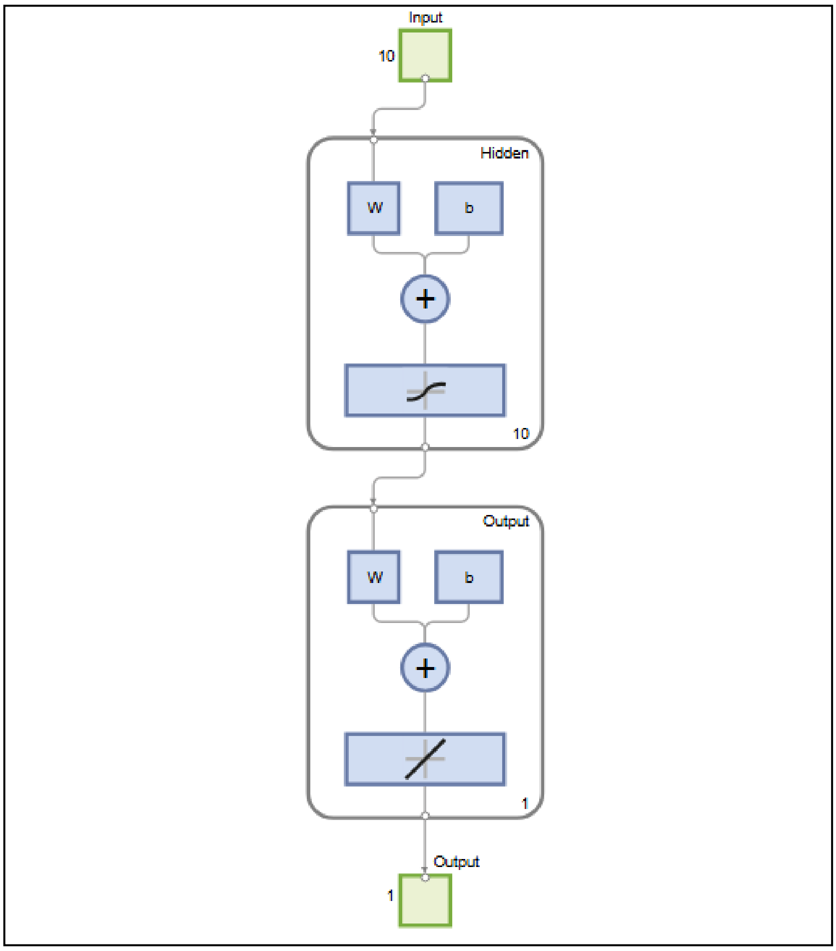

Fig 5. Structure of the Network in Matlab Online
(Source : prepared by us)

The measured regression value reached R=1, indicating optimal accuracy in the model's predictions. This exceptional performance is directly attributable to the meticulously designed geometry of the network, as illustrated in the ***Fig 6***. The R=1 value reflects a perfect correlation between the network's predictions and the actual values, thus highlighting the effectiveness of the network's structure in capturing the complex dynamics of the analyzed data. This level of accuracy demonstrates the robustness of the model and the relevance of the methodological choices made during its design.

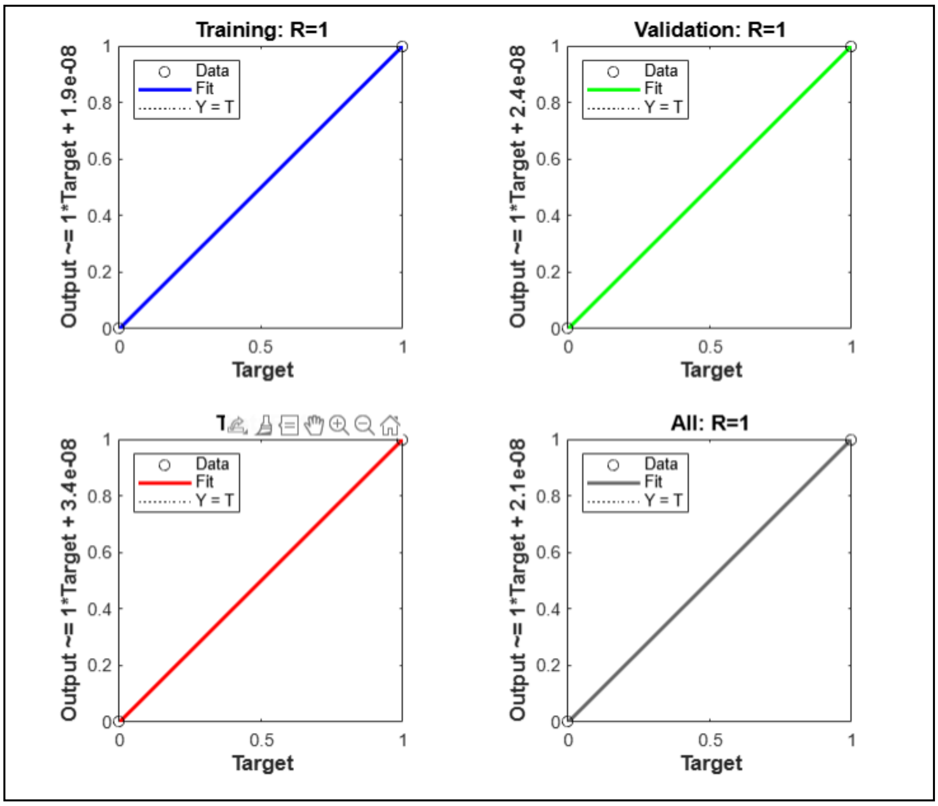

Fig 6. Regression Analysis of Neural Network Training in Matlab Online (Source : prepared by us)

To analyze and present the differences between the network's outputs and the target values, we employed the MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) methods. These methods are essential for evaluating the accuracy of the model's predictions.

- MSE (Mean Squared Error) : MSE measures the average of the squared differences between the actual values and the predicted values . It is calculated using the formula :

$$MSE = \frac{\sum_{i=1}^{T}(y_i - \hat{y}_i)}{T}$$

This measure evaluates the model's performance by penalizing larger errors more heavily, thus providing a rigorous assessment of the overall accuracy of the predictions.

- RMSE (Root Mean Squared Error): RMSE is the square root of the MSE:

$$RMSE = \sqrt{MSE}$$

This criterion expresses the average error in the same units as the original data, making interpretation and comparison of model performance easier. A lower RMSE indicates better accuracy.

We selected the model with the lowest prediction error, determined by the MSE and RMSE values. The model with the smallest error is considered the most effective, as it minimizes the differences between the actual and predicted values. This approach ensures that we choose the most accurate model.

RSME is the positive root of SME, in which T is the number of input variables and y_t and $\hat{y}_t$ are real and predicted values of the intended variables respectively. Indeed,

$y_t - \hat{y}_t$ Shows the differences between these two amounts. In the following, we figured out the result.

Consequently, ***Fig 7*** illustrates the network's optimal performance, achieved at epoch 16. At this stage of training, the network demonstrated its best predictive capabilities, as evidenced by the performance metrics displayed. This epoch represents the point at which the model reached the highest level of accuracy and stability, thereby optimizing its effectiveness in the regression

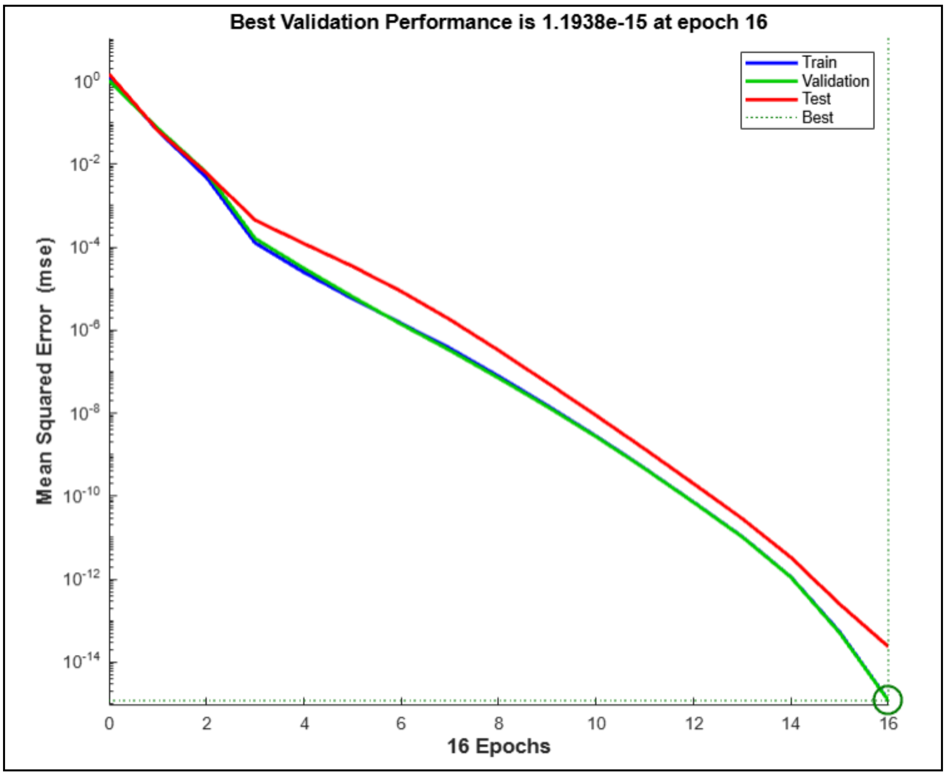

Fig 7. Performance of Neural Network Training in Matlab Online
(Source : prepared by us)

task. This observation underscores the importance of properly tuning training parameters to maximize the neural network's performance.

Fig 8 illustrates the histogram or distribution of errors between the target values and the predicted values for the training, testing, and validation phases. The errors are normally distributed and centered around zero, indicating that the model's predictions are generally accurate and aligned with the target values.

However, we observed several test data sets with significant errors, reaching up to 20%. These data sets represent outliers compared to the general distribution of errors. Nevertheless, it is important to note that the majority of errors in the test set remained within a range of less than 10%. This concentration of errors around zero and within a relatively narrow range demonstrates that, despite some exceptions, the model provides generally reliable and accurate predictions.

These observations highlight the overall performance of the model as well as potential areas fr improvement, especially concerning data sets with larger errors.

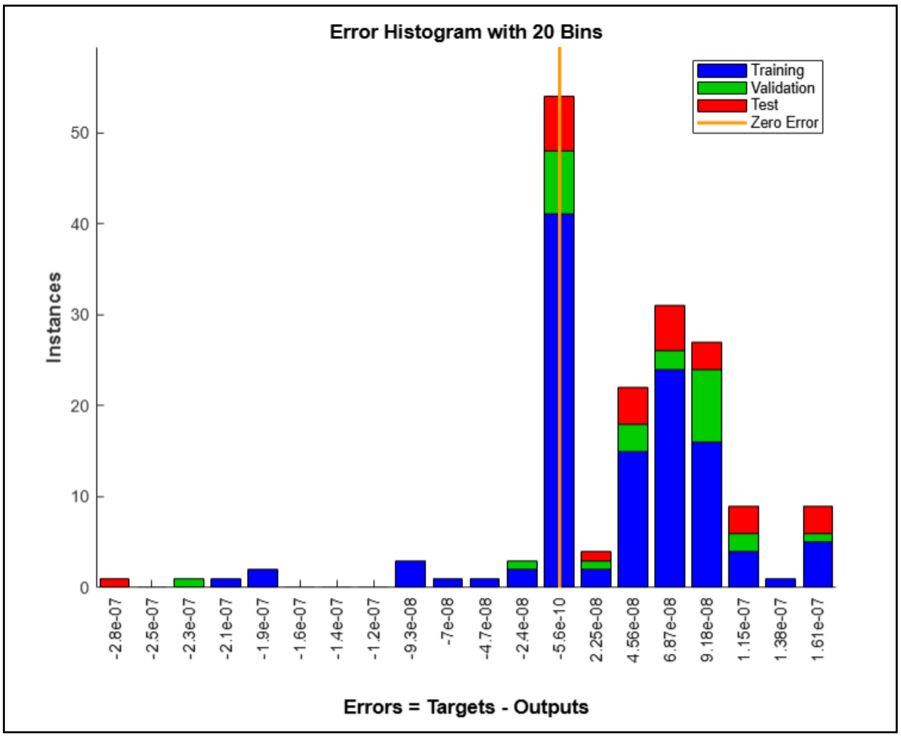

Fig 8. Histogram of error distributions for ANN training, validation, and testing, generated in MATLAB Online (Source : prepared by us)

The gradient represents the slope of the tangent to the function's curve at a given point. It indicates how steeply the function is increasing at that point. A high gradient signifies a significant rate of increase in the function’s value in the direction of the gradient, which is important for effectively adjusting the model’s parameters during training.

The parameter serves as a control factor in the backpropagation neural network we modeled. It is crucial in regulating the learning rate of the network. Proper selection of μ is vital because it directly affects error convergence. A μ that is too high can lead to oscillations and divergence in learning, while a μ that is too low may slow down convergence, making the learning process excessively lengthy.

Validation checks are used to terminate the training of the neural network when there is no significant improvement in performance on the validation data. This method helps prevent overfitting by stopping training once validation performance plateaus. The number of validation checks required will depend on the number of successive iterations performed by the neural network. More iterations typically mean that multiple validation checks will be needed to ensure the model continues to learn effectively and does not overfit as demonstrated in ***Fig 9***.

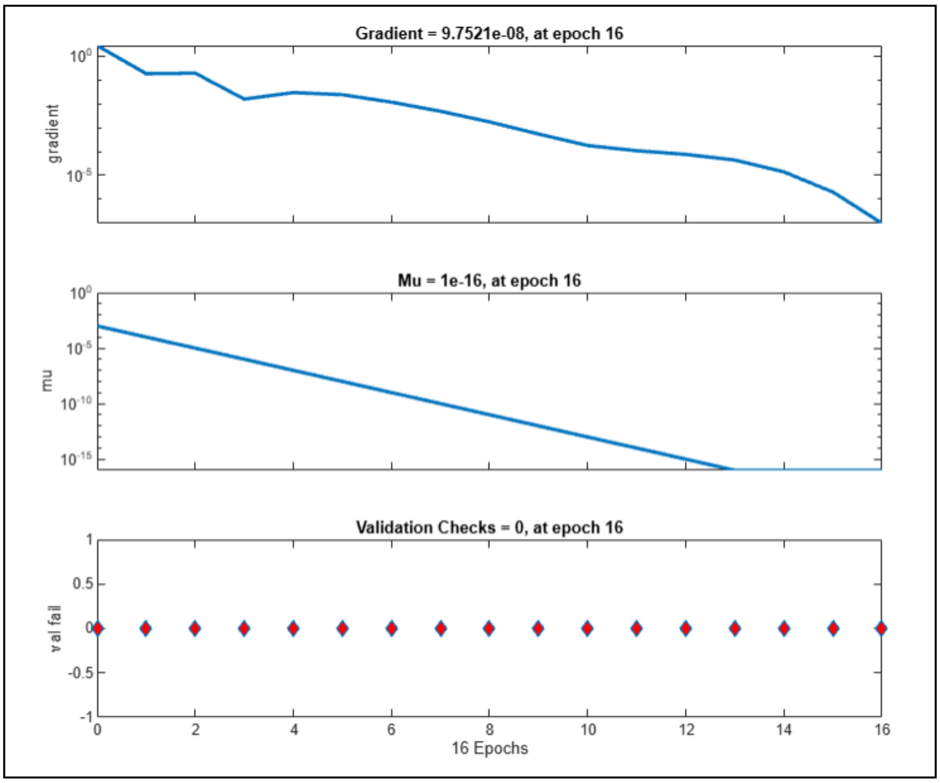

Fig 9. Plotting gradient values μ, and validation failures in MATLAB Online
(Source : prepared by us)

In ***Fig 10***, we have a representation of our database in the form of a neural network modeled in SPSS version 29. This network consists of a single layer, where the inputs are the variables ***(X1,…,X10)*** and the output is represented by ***Y***.

- Inputs ***(X1,…,X10)***: These variables represent different characteristics or attributes of our database. They provide the network with information.
- Output ***(Y)***: The output Y is a binary variable that can take two values:

Y=0: Indicates that the convention is not executed.

Y=1: Indicates that the convention is executed.

The neural network uses the inputs to calculate the output ***Y***, which predicts whether the convention will be executed or not, based on the given characteristics. The model captures the complex relationships between the input variables and the final binary decision (whether the convention is executed or not).

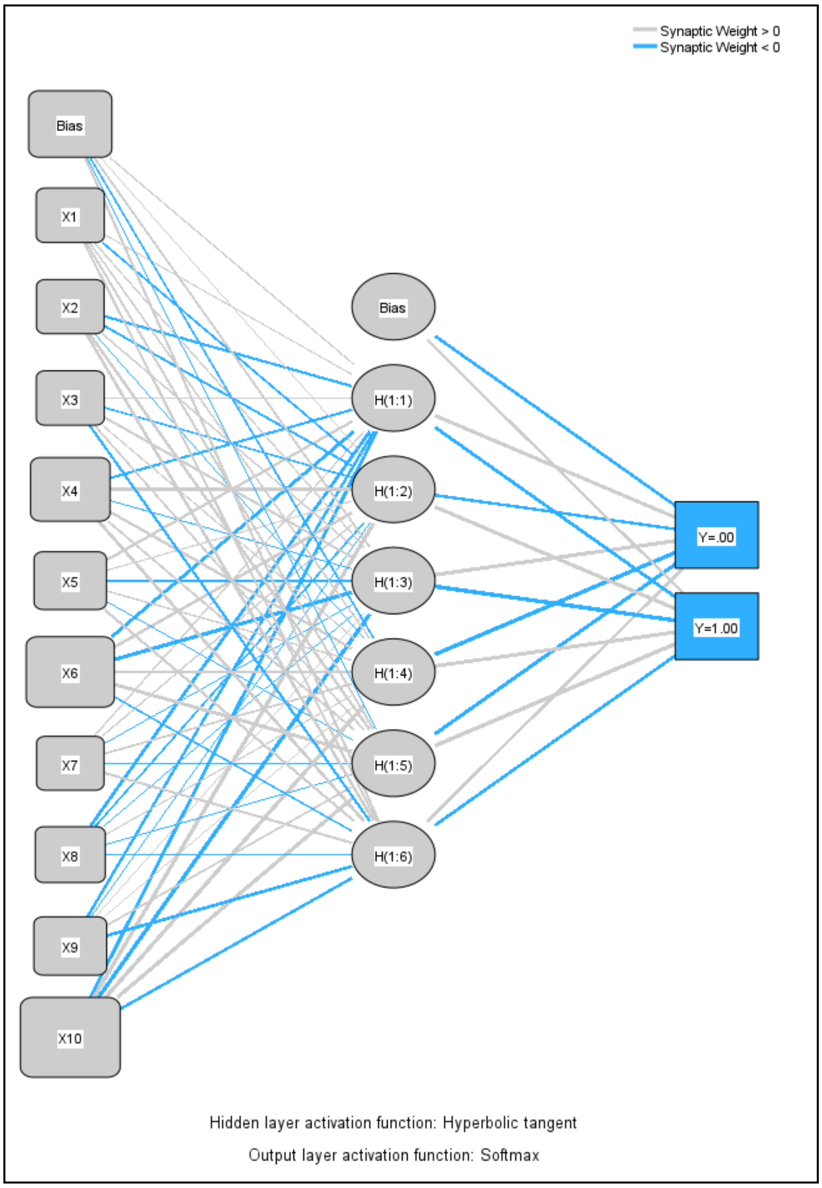

Fig 10. Deep Neural Network Model of the Database in SPSS

(Source : prepared by us)

The ***Table 2*** provides a summary of the performance of a neural network model, focusing on both the training and testing phases.

- **Training Phase:**

Sum of Squares Error (1.031): This metric indicates the total squared error during the training phase. A lower value generally indicates better model performance, but it is important to compare this with the testing error to evaluate the model's generalization capability.

Percent Incorrect Predictions (1.6%): This value shows that 1.6% of the predictions made by the model during training were incorrect, which is relatively low, suggesting that the model performed well on the training data.

Training Time (0:00:00.19): The model took 0.19 seconds to complete the training process, indicating a quick training phase, likely due to the simplicity of the model or the small size of the data set.

- **Testing Phase:**

Sum of Squares Error (0.297): The error during the testing phase is significantly lower than during training. This indicates that the model generalizes well to unseen data, which is a positive outcome.

Percent Incorrect Predictions (0.0%): The model made no incorrect predictions on the testing data, which suggests excellent performance on this dataset.

The number of hidden units (neurons in the hidden layer) was optimized based on the testing data. The best configuration was selected based on minimizing the error in the testing phase, which helps to prevent overfitting and ensures that the model generalizes well.

The model appears to perform exceptionally well, particularly on the testing data, where it made no incorrect predictions and achieved a lower error than in the training phase. The optimization of hidden units based on testing data suggests a careful balance between complexity and performance.

Table 2. Model Evaluation: Errors and Accuracy in SPSS

Model Summary

Training	Sum of Squares Error	1,031
	Percent Incorrect Predictions	1,6%
	Training Time	0:00:00.19
Testing	Sum of Squares Error	,297[a]
	Percent Incorrect Predictions	0,0%

Dependent Variable: Y

a. The number of hidden units is determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

Source : prepared by us

The ***Fig 11*** indicates that variable X5 has the highest normalized importance at 100%, followed by X10 at 74.8% and X6 at 59.8%, while variables X1 and X8 have the lowest normalized importance at 4.3% and 8.2%, respectively.

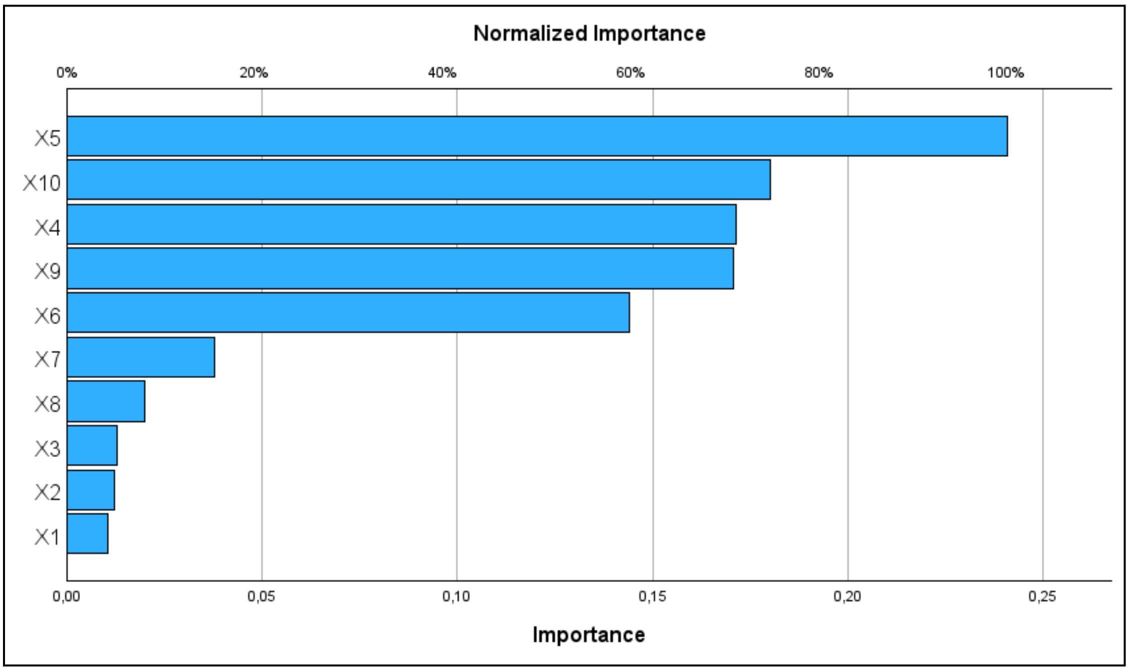

Fig 11. Importance and Normalized Importance of Independent Variables in the Model in SPSS

(Source : prepared by us)

5 Conclusion

The implementation of conventions represents a crucial issue for regional development, marked by its complexity and direct impact on the growth and cohesion of the affected territories. This research has highlighted the importance of rigorous data collection, based on official documents, reports, and regional statistics, to provide a solid foundation for in-depth analysis. This approach has enabled the formulation of practical recommendations aimed at improving the implementation processes of conventions and promoting balanced and sustainable regional development.

Data analysis was conducted using advanced data mining tools, effectively correcting anomalies and missing elements. After rigorous processing, the initial dataset was refined to a subset of 170 conventions for which complete information was available. Despite the efforts made, certain limitations were encountered during the data collection phase, hindering the acquisition of all necessary information for each convention. However, these limitations were taken into account to minimize their impact on the final results.

The next stage of analysis was conducted in Matlab Online and SPSS version 29, where a multi-layer perceptron deep neural network was employed to capture non-linear relationships within the data. The developed model demonstrated exceptional accuracy, with a regression value of R=1, indicating a perfect correlation between the network's predictions and the actual values. This result reflects the robustness of the model and the relevance of the methodological choices made.

However, this research presents certain limitations, notably the challenges related to the complete data collection and the presence of test datasets with significant errors. These observations underscore the importance of continuing efforts to improve data quality and refine analytical models.

Future work perspectives include extending the study to other regions to verify the model's robustness, integrating qualitative data to enrich the analysis, and enhancing analytical methods with more advanced machine learning techniques. Additionally, a longitudinal follow-up of conventions would allow testing the long-term robustness of the model's predictions and identifying factors influencing the evolution of conventions over time.

Although limitations have been identified, this research offers promising prospects for optimizing the implementation of conventions and contributing to more balanced and sustainable regional development.

6 References

A. K. M. Mahbubur Rahman, M. Z. (2021). *Applying State-of-the-Art Deep-Learning Methods to Classify Urban Cities of the Developing World* (Vol. 21). doi:10.3390/s21227469

ACKLEY, D. H. (1985). A learning algorithm for boltzmann machines. *Cognitive Science, 9*(1), 147-169. doi:10.1016/S0364-0213(85)80012-4

Aissa, & Ben, H. (2001). *" Xième Conférence de l'Association Internationale de Management Stratégique, 27 Quelle Méthodologie de Recherche Appropriée Pour Une Construction de La Recherche En Gestion ?*

Alnaser, A. S. (2012). Assessing the relationship between higher education service quality dimensions and student satisfaction. *Australian Journal of Basic and Applied Sciences 6(1)*, 156-164.

Alsnaser, A. S., & Almsafir, M. k. (2014). Service quality dimensions and students satisfaction. *journal of advanced social research vol 4*, 01-17.

Ansoumane, S., & Alain, G. (2020, février). *Réhabilitation et Extension du réseau de transport et distribution de Conakry.* Conakry.

Asmaa Faris, M. E. (2024, aout 14). Exploring the Impact of Artificial Intelligence and Machine Learning on Predicting Outcomes in Regional Development Conventions: A Case Study of the Tanger-Tetouan-Al Hoceïma Region, Morocco. *Global Journal of Economics and Business, 14*(4), 387 - 408. doi:10.31559/GJEB2024.14.4.6

BANQUE MONDIALE. (2021). *Etude pour le développement d'un atlas du potentiel hydroélectrique de la République de Guinée.* Conakry.

Becket, N., & Brookes, M. (2006). «Evaluating quality management in university departments ». *Quality Assurance in Education. Vol.14, N°2,*, p.123-142.

Bénoit, R., Arnaud, D., & Bruno, F. (2021). Production d'énergie électrique à partir des sources renouvelables. *Hermès sciences publications,*.

BISHOP, C. M. (1995). Neural Networks for Pattern Recognition.

Bitner, M. (1990). Evaluating service encounters : the effects of physical surroundings and employee responses. *Journal of Marketing, 2*(54), 69-82.

Bolton, R. e. (1991). A multistage model of customers' assessments of service quality and value. *Journal of Consumer Research, 4*(17), 375-384.

BOSER, B. S. (1991). analog neural network processor with programmable topology. *IEEE Journal of Solid-State Circuits, 26*(12), 2017-2025. doi:10.1109/4.104196

Bourgeon, D., & Kruger, A. (2010). L'effet de bouche à oreille et le processus de choix du spectateur cinématographique.

Cantin, J., & Rocheleau, L. (2006). Sondage sur les attentes et la satisfaction des usagers hospitalisés à l'égard des services offerts à l'Hôpital Louis-H. Lafontaine,.

Chakor, & Amrani. (2019). *Revue Internationale du Marketing et Management Stratégique, Volume 1, N°4, Octobre-Décembre 2019*, 226.

Chenhui Ding, C. L. (2021). *Digital Economy, Technological Innovation and High-Quality Economic Development: Based on Spatial Effect and Mediation Effect* (Vol. 14). doi:10.3390/su14010216

Cherquaoui, W., Chroqui, R., & Okar, C. (2015). Influence de la qualité de l'enseignement superieur sur la satisfaction des etudiants.

Chiheb, F. F. (2017). Predicting students performance using decision trees: Case of an Algerian University. *International Conference on Mathematics and Information Technology (ICMIT)*, (pp. 113–121).

COLLOC, J. (2000). Les apports réciproques de la modélisation objet et de la connaissance médicale. *HDR*.

CORNUÉJOLS, A. M. (2018). Apprentissage artificiel: deep learning, concepts et algorithmes.

Cronin, & Taylor. (1992). *Measuring Service Quality: A Reexamination and Extension The Journal of Marketing*,, 55-68.

Cronin, Brady, & Hult. (2000). *Assessing the effects of quality : Journal of Retailing*.

Cronin, J. e. (1992). Measuring service quality : a reexamination and extension. *ournal of Marketing, 3*(56), 55-68.

Datta, K. S., & Vardhan, J. (2017). A SERVQUAL-Based Framework for Assessing Quality of International Branch Campuses in UAE: A Management Students' Perspective. *SAGE January-March* , 1-9.

(s.d.). *Décret : D/2017/241/PRG/SGG du 30 juin 2017.*

Dellarocas, C. ((2003),). The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms,. *Management Science*, 49 (10), 1401–1424.

Domashova, A. O. (2020). Identification of public procurement contracts with a high risk of non-performance based on neural networks. *Procedia Computer Science, 169*, 795–799. doi:10.1016/j.procs.2020.02.161

DRIANCOURT, X. (1994). *Optimisation par descente de gradient stochastique de systemes modulaires combinant reseaux de neurones et programmation dynamique. Application a la reconnaissance de la parole*. (Paris: Université Paris 11) Récupéré sur http://www.theses.fr/1994PA112203

EDG. (2020). *Rapport annuel des activités de 2016, 2017 et 2018, janvier 2020.* Conakry.

Engel, Blackwell, & Kegerreis. (1969). *Journal of Advertising Research Research*, 3-8.

F., I. (2011). Satisfaction de la clientèle des institutions financières : analyse comparative de la satisfaction des clients des banques commerciales et des institutions de micro-finance,. *Mémoire inédit, Faculté des Sciences Economiques et de Gestion*.

Frédérique, B., & al. (2009). Etude de la satisfaction de la clientèle à l'Hôpital de Fort-Liberté,. *Travail inédit*.

Gauthier. (2001). Mesurer la satisfaction de sa clientèle pour mieux répondre à ses attentes. *Réseau Circum Inc*.

Georges, M. (1984). A pure Birth Model of Optimal Advertising with Word-of-mouth . *Marketing sciences , vol 3*, 169-178.

Gmach, O. (2009). *L'impact de l'approche relationnelle sur la communication du bouche à oreille dans le domaine des services electroniques.* montréal.

H. Huang, Q. Z. (2020). Deep learning for urban big data analytics: A survey. *International Journal of Information Management, 50*, 413-423.

HINTON, G. E. (2012). *Improving neural networks by preventing co-adaptation of feature detectors.* Récupéré sur arXiv:1207.0580 [cs]: http://arxiv.org/abs/1207.0580.

HINTON, G. E.-W. (2006). A Fast Learning Algorithm for Deep Belief Nets. *Neural Computation, 18*(7), 1527-1554. doi:10.1162/neco.2006.18.7.1527

I. Goodfellow, Y. B. (2016). Deep learning. *MIT Press*.

IONOS. (2021, 9 15). *Quelles sont les différences entre le Deep learning et le Machine learning ?* (Digitalguide) Récupéré sur IONOS: c

IRENA. (2019). *Rapport de la planification et perspectives pour les énergies renouvelables de l'Afrique de l'Ouest,.*

J. Gallego, G. R. (2021). Preventing rather than punishing: An early warning model of malfeasance in public. *International Journal of Forecasting, 37*(1), 360–377. doi:10.1016/j.ijforecast.2020.06.006

Ji Luo, G. W. (2022). *Transport infrastructure connectivity and conflict resolution: a machine learning analysis* (Vol. 34).

Julia, B. (1990). Enhanced Explainations of Word of Mouth Communications : The Power of Relationships. *research in Consumer Behavior , vol 4*, 51-83.

K. Sahoo, A. K. (2019). Exploratory data analysis using python. *International Journal of*

Innovative Technology and Exploring Engineering, 8(12), 4727–4735. doi:10.35940/ijitee.L3591.1081219

Katz, E. e. (1955). Personal influence: the part played by people in the flow of mass communications, . *Glencoe: The Free Press.*

Kebede, M. D. (2017). Predicting CD4 count changes among patients on antiretroviral treatment: Application of data mining techniques. *Computer Methods and Programs in Biomedicine, 152*, 149–157.

Kripak, J. D. (2021). pplication of machine learning methods for risk analysis of unfavorable outcome of government procurement procedure in building and grounds maintenance domain. *Procedia Computer Science, 190*, 171–177. doi:10.1016/j.procs.2021.06.022

L. REBAI, “. (2019). Evaluation d’un projet d’investissement Cas pratique : CEVITAL.”. 13-18.

LE CUN, Y. (1985). Une procedure d’apprentissage pour reseau a seuil asymmetrique. *Proceedings of Cognitiva 85*, 599-604.

LE CUN, Y. B. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278-2324. doi:10.1109/5.726791

Le Roy, C. (2004). Le comportement des étudiants sur le marché du téléphone mobile : inertie, captivité ou fidélité ? *Papier no 66*.

LESHNO, M. L. (1993). Multilayer feedforward networks with a nonpolynomial activation function can approximate any function. *Neural Networks, 6*(6), 861-867. doi:10.1016/S0893-6080(05)80131-5

M. J. García Rodríguez, V. R.-M.-P. (2022). Collusion detection in public procurement auctions with machine learning algorithms. *Automation in Construction, 133*. doi:10.1016/j.autcon.2021.104047

Marc, w., Christine, G.-Z., & Hèlène, H. (2014). Perception de la qualité d’une formation universitaire par les étudiants : étude comparative selon le mode d’orientation et l’ancienneté dans le cursus. *Mesure et évaluation en éducation / Volume 37 / numéro 1*.

MCCULLOCH, W. S. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics, 5*(4), 115-133. doi:10.1007/BF02478259

MEH. (2020). *Rapport des études préliminaires du plan directeur de développement des infrastructures de production et de transport,*. Conakry.

Michèle, L.-O., Grazia, S. G., & Anne-Catherine, W. (2011). " Les mondes universitaires face au marché. Circulation des savoirs et pratiques des acteurs ".

Mohamed Mansour, K. (2012). , *Eau et Electricité : Solution durable pour la Guinée.* Conakry.

Morais, A. H. (2017). Predicting the need of Neonatal Resuscitation using Data Mining. *Procedia Computer Science, 113,* 571–576.

N. Kussul, M. L. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters, 14*(5), 778-782.

Nathalie, T. (2020.). *Rôle de l'EIES dans la recherche des solutions socialement acceptables, TRACTEBELENGIES l.*

Nguyen. (2012). Viêtnam: Faculté de gestion d'entreprises, Institut universitaire de technologie, de poste et de télécommunication.

Nikos, S., Daniel, P., Lucus, M., Mohamed, Y., & Sokona, G. (2016). *Rapport de progrès régionaux sur les énergies renouvelables, l'éfficacité énergétique et l'accès à l'énergie dans la région de la CEDEAO.*

Oliveira, D. F. (2017). Towards an Intelligent Systems to Predict Nosocomial Infections in Intensive Care. *5th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW),* (pp. 150–155).

Owlia, & Aspinwall. (1996). « Quality in higher education. A survey ». *Total Quality Management. Vol.7, N°2,* p.161-171.

Parasuraman, & coll. (1988). *« SERVQUAL: A Multiple-Item Scale For Measuring Consumer Perceptions Of Service Quality ».Journal of Retailing. Vol.64, N°1.,* p.12-40.

Parasuraman, A., Berry, L. L., & Zeithaml, V. A. (1985). A Conceptual Model of Service Quality and its Implications for Future Research. *Journal of Marketing, 64*(1), 12- 40.

Parasuraman, Ananthanarayanan, Leonard, B., Zeithaml, & Valerie. (1988). *ServQual : a multiple item scale for measuring consumer perceptions of service qualitJournal of Retailing, 64*(1), 12-44.

Park. (2007). *Les déterminants de la satisfaction et de la fidélité du visiteur fréquentant le musée national d'art contemporain en Corée du Sud,.*

Pierre, S. (2011). L'aménagement hydroélectrique de Souapiti sur le fleuve Konkouré, Guinée. *la houille Blanche*, 415-425.

Poh, C. Q. (2018). Safety leading indicators for construction sites: A machine learning approach. *Automation in Construction, 93,* 375–386.

Putpuek, N. N. (2018). Comparative Study of Prediction Models for Final GPA Score: A Case Study of Rajabhat Rajanagarindra University. *2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS)*, 92–97.

Rivière. (2009). *« Les effets des stratégies d'enrichissement de produits sur la valeur perçue d'un bien complexe. Une application au secteur automobile »,.* Université François-Rabelais de Tours, novembre.: Thèse de Doctorat en Sciences de Gestion,.

Rüdiger Wirth, J. H. (2000). CRISP-DM: Towards a Standard Process Model for Data. Récupéré sur https://www.cs.unibo.it/~danilo.montesi/CBD/Beatriz/10.1.1.198.5133.pdf

RUMELHART, D. E. (1986). Learning internal representations by error propagation. *arallel distributed processing: explorations in the microstructure of cognition, 1*, 318–362.

Rupin, Kahombera, B., & Duranton, F. (2018). SATISFACTION DES ETUDIANTS DANS UNE INSTITUTION D'ENSEIGNEMENT UNIVERSITAIRE. *Cahiers de Psychologie Cognitive - Current Psychology of Cognition, Marseille: ADRSC,.*

RUSSELL, S. J. (2010). Intelligence artificielle: avec plus de 500 exercices.

S. P. Chatzis, V. S. (2018). Forecasting stock market crises using deep learning. *Journal of Financial Markets, 42*, 33-47.

Schnell, J. C. (2019). Data mining in lithium-ion battery cell production. *Journal of Power Sources, 413*, 360–366.

Sékou, F. (2013). *Expériences de réinstallation des populations de Garafiri et de Kaléta, Atelier national.*

Selly, C., & Abdelkader, B. (2018). valorisation des ressources energétique en Guinée en vue d'un développement économmique, social et durable. *journal of water and environmental sciences*, 106-114.

Skida, Guelma, Biskra, Oum, & Bouaghi. (2010). Les enjeux de l'assurence qualité dans l'enseignement superieur. *le consortium des université.*

Soliman, G. A.-N. (2017). Predicting all star player in the national basketball association using random forest. *Intelligent Systems Conference (IntelliSys)*, (pp. 706–713).

T. Inan, T. N. (2022). A Machine Learning Study to Enhance Project Cost Forecasting. *IFAC-PapersOnLine, 55*(10), 3286–3291. doi:10.1016/j.ifacol.2022.10.127

Talingdan, J. A. (2019). Performance comparison of different classification algorithms for household poverty classification. *4th International Conference on Information Systems Engineering* (pp. 11–15). ICISE. doi:10.1109/ICISE.2019.00010

Teas, R. (1993). Expectations, performance evaluation, and consumers' perceptions of quality. *ournal of Marketing., 4*(57), 18-34.

Thietard, R. (2007). Méthodes de recherche en management. Dunod, 3ème édition.

Thonhauser, & Passmore. (2006). « ISO 9000 In Education: A Comparison Between The

United States And England ». *Research in Comparative and International Education. Vol.1, N°2*, p.156-73.

U. Park, Y. K. (2022). A Stacking Heterogeneous Ensemble Learning Method for the Prediction of Building. *Applied Sciences (Switzerland), 12*(19). doi:10.3390/app12199729

WAIBEL, A. H. (1989). Phoneme recognition using time-delay neural networks. *IEEE Transactions on Acoustics, Speech, and Signal Processing, 37*(3), 328-339. doi:10.1109/29.21701

Werbler, & Harris. (2008). Online Consumer Reviews Significantly Impact Consumer Purchasing Decisions,. *New Opinion Research Corporation Survey Finds. Oct 6,*.

X. Shi, Z. C. (2015). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. *Advances in Neural Information Processing Systems, 28*, 802-810.

Zhang, C. L. (2019). Urbanization prediction based on deep learning. *Sustainability, 11*(5), 1377.