ISSN: 0975-833X

Available online at http://www.journalcra.com

INTERNATIONAL JOURNAL OF CURRENT RESEARCH

International Journal of Current Research

Vol. 16, Issue, 09, pp.29987-29994, September, 2024

DOI: https://doi.org/10.24941/ijcr.47872.09.2024

RESEARCH ARTICLE

PROPOSAL OF AN AGRICULTURAL NEURAL NETWORK MODEL FOR THE PREDICTION OF COMMODITY SALES PRICES

KANGA Koffi[1,*], KAMAGATE Beman Hamidja[2], BROU Aguié Pacome Bertrand[3], ADAMA Konaté[4] and OUMTANAGA Souleymane[5]

[1]Doctor in computer science, specializing in software and database engineering: INPHB doctoral school Teacher and Researcher at ESATIC (African Higher School of ICT: Republic of Ivory Coast); [2] Doctor of Computer Science Teacher – researcher at ESATIC (African Higher School of ICT: Republic of Ivory Coast); [3] Doctor in computer Science specializing in network and cyber-security at INPHB doctoral school, Teacher – researcher at ESATIC(African Higher School of ICT: Republic of Ivory Coast); [4] General manager of African Higher School of ICT: Republic of Ivory Coast); [5]Lecturer at INPHB Yamoussoukro Republic of Ivory Coast

ARTICLE INFO

Article History:
Received 20th June, 2024
Received in revised form
19th July, 2024
Accepted 19th August, 2024
Published online 30th September, 2024

Key Words
Neural networks, prediction models, machine learning , deep learning

***Corresponding author:**
KANGA Koffi

ABSTRACT

In this paper, we are proposing a neural network model applied to the agricultural domain for predicting the selling price of raw materials. To achieve our objective, we have reviewed the various works on cost prediction related to Depp to our knowledge. The different types of neural network were also presented. Our approach to implementing this neural network consisted in collecting, preparing the data making up the network inputs, selecting and designing our neural network model. An architecture defining the different layers of the network and a mathematical model were proposed. A pseudo code was also proposed, taking as input a dataset containing historical commodity prices, economic variables (inflation, interest rates, etc.), geopolitical variables (sanctions, conflicts, etc.) and target sales prices (to be predicted). Simulation results of our proposal on a dataset, based on the kola nut cultivation domain has shown that our model can instantly predict raw material sales prices.

Citation: KANGA Koffi, KAMAGATE Beman Hamidja, BROU Aguié Pacome Bertrand, ADAMA Konaté et al. 2024. "Proposal of an agricultural neural network model for the prediction of commodity sales prices.". *International Journal of Current Research*, 16, (09), 29987-29994.

INTRODUCTION

Talking about neural networks to predict the costs of agricultural raw materials deserves some explanation. In fact, for decades several countries have based their development on agriculture. These countries have set up organizations and governance systems to improve producers' incomes and their various gross domestic products. At times, the various products from these agricultural organizations have difficulty in having visibility of production costs, sales prices and other costs over time. Thus, the problem of finding a technique to predict the various costs deserves to be addressed in order to find an effective solution. Also, in the agricultural field, the determination of raw material prices on the market would take into account the following factors: historical price trends, currency fluctuations, economic conditions (supply, demand, inflation, etc.), geopolitical events, transportation and production costs. All these information and data could come from financial databases, global economic statistics and sector indices (e.g. Brent for oil). As for neural networks, they are etymologically part of the field of biology (we speak of biological neuron). In computer science, neural networks were designed with the aim of mathematically modeling the processing of information in the same way as biological neurons found in the cortex of mammals. Nowadays, their biological realism matters little and it is rather their efficiency in modeling complex and non-linear relationships that makes them successful (Azencott, 2022). They come in the forms presented in Table 1.

Furthermore, the organization of this paper, which aims to set up a neural network model applied to the agricultural field, is as follows:

- Section 2, we will present the state of the art
- Section 3, we will identify our problem

- In section 4, we will illustrate our contribution
- Section 5 is devoted to a discussion and we will end with a conclusion in Section 6. In that section, we will outline some perspectives.

Table 1.The different forms of neural networks and their applications

Type of neural network	Role	Use
Feedforward Neural Networks (FFNN)	Data flows in one direction only, from input to output.	Used for classification and regression.
Convolutional Neural Networks (CNN)	Designed to process grid-structured data, such as images.	Use convolutional layers to extract features.
Recurrent Neural Networks (RNN)	Suitable for sequential and textual data, time series.	Have recurrent connections to keep a memory of previous states.
Long Short-Term Memory (LSTM)	A variant of RNNs, capable of retaining information over long periods.	Used in applications like machine translation and sentiment analysis.
Back propagation neural networks	Learning method for adjusting weights in neural networks.	Uses back propagation of error to optimize performance.
Generative Adversarial Networks (GANs)	Composed of two networks (a generator and a discriminator) which compete against each other.	Used to generate new data from random noise.
Auto encoders	Unsupervised networks that learn to encode input data into a more compact format and then decode it.	Used for dimensionality reduction or anomaly detection.
Attention Neural Networks	Use attention mechanisms to focus on certain parts of the input data.	Widely used in natural language processing(eg: Transformers).
Deep Neural Networks (DNN)	Composed of several hidden layers, allowing complex representations to be learned.	In the prediction

State of the art: In theexisting literature, several good works have been carried out. In this part of our work, we presented those relating to the prediction of costs in connection with Depp Learning and neural networks to our knowledge. Thus in (2), the authors have contributed to the estimation of the market value of real estate properties. To achieve their objective, which was based on regression, they have used three models, which are:

- The definition of a first model based on models using set designer learning techniques (BAGGING) and this by applying random forest algorithms,
- The construction of a second model using another set learning technique,
- The use of models using neural networks. The results of the implementation of these 3 models showed that the model based on neural networks produces better results compared to the first two (Bellahmer, 2020). However, the work discussed is not in the field of agriculture where very often the results depend on several environmental and climatic factors including rainfall.

In (Fatima, 2023), Fatima et al, work to use a Deep Learning model to predict time series relating to energy consumption in the gas industry. To achieve their objective, the authors used the eviews and matlab R2023 programs in data processing and obtaining results. According to the authors, the techniques of using neural networks to make predictions produce satisfactory results compared to other methods. When analyzing their excellent work, it does not fall within the agricultural field. A field where climatic hazards and market price fluctuations are the key words. Still in the search for a solution to the task of predicting phenomena, Khelouat et al in (2020), make a foray into the field of cryptocurrency by seeking to anticipate its value using machine learning. In their approach, they collected relevant data in sufficient quantities; These are cleaned, they are then grouped together to form a large organized database that will later be divided into training, validation and test data. Subsequently, they implemented the algorithms and models most used in most financial market studies. Thus, three models based on artificial neural networks selected for their performance during the training phase were used. The quality of these 3 models was tested by making comparisons between them. Despite this fact, the work of these authors was applied in a different field than that of agriculture.

In (Hala, 2023), Hala et al chose to conduct studies to predict oil prices using the analytical methods "ARMA" and "ARIMA". Despite the considerable contributions of their work, certain shortcomings relating to the field of application are noted. These shortcomings are:

- The agricultural sector is not taken into account
- Their prediction technique does not take into account modern prediction tools such as deep learning and its various associated algorithms.

Fiordaliso et al in (1997), use artificial neural networks (MLP) for the prediction of the price of a negotiable option (in the field of finance). Thus several architectures have been used and present various forms of difficulties as to their manipulation. The results obtained with one or more explanatory variables show that the use of a single variable does not give convincing results compared to the use of several variables. Also like the other authors mentioned above, this work of Fiordaliso et al does not take into account the specific character that is agriculture.

Problematic: Based on all of the above , it appears that excellent research works have been carried out. Some of them have contributed to price prediction in various fields (finance, gas, real estate, etc.). Also, some work used traditional prediction tools linked to statistical methods without, however, taking into account or comparing these methods to the tools offered by artificial intelligence; namely machine learning, deep learning and its associated prediction techniques.

In view of the above, and in an effort to improve the service offered by agricultural nations to their populations, what could be the effective method of predicting future sales prices so that producers can have visibility of their activity? Also, in the era of globalization and with the advent of social networks, what machine learning tools (architecture and associated algorithm) should be implemented for effective prediction of agricultural product prices?

Contribution: In a previous paper, we proposed a data model for commodity price prediction in a business intelligence context. Thus, in order to have a complete price prediction system in the agricultural field, our present contribution aims to set up a sales price prediction method using deep neural networks in the agricultural field. In this field, price fixing or determination of sales prices is a function of various parameters such as historical price trends, currency fluctuations, economic conditions (supply, demand, inflation, etc.), geopolitical events, transportation and production costs of the various products. Furthermore, the products for which we seek to predict sales prices come from different plantations, each with an estimated area and production. All those information are available and can be consulted from various data sources such as financial databases, national and global economic statistics, sector indices (e.g. Brent for oil).

Implementation approach for price prediction through our agricultural neuron

Our adopted method for implementation includes the following points:

Data collection and preparation: Here we have collected data from agricultural plots, each with an area and a production that is a function of the area. The data collected, in their preparation phase, will be divided into 3 sets which are the training data (train) of our model, the validation data (validation) and the test data (test).

The choice and design of the neural network model: To choose a neural network model, we presented in Table 2 the different forms of neural network and their role or possibilities. In view of what is presented in Table 2, and according to the research results of (18), we have opted for recurrent neural networks (RNN) because they allow us to best model time series.

Table 2. Different forms of neural network

Shape	Roles or possibilities
Simple Deep Neural Network (DNN) Model	A neural network with multiple dense layers. Use non-linear layers (ReLU) to capture complex relationships. Adapt the network depth according to the complexity of the data.
Model with recurrent network (RNN, LSTM or GRU)	Use a recurrent network (RNN) model or its variants like LSTM (Long Short- Term Memory) or GRU (Gated Recurrent Units). These models are suitable for time series because they can memorize past relationships to predict future events.
Convolutional Neural Network CNN component	Convolutional networks can be used to capture local patterns in data (local trends, volatility spikes, etc.). A hybrid model combining CNN and RNN can give good results in some cases.

Training the chosen neural network model: Here, this step consists of adjusting the model parameters (weight and bias, area and production in our case) so that it can accurately predict an output (a price) from an input (the area, tonnages, previous prices characteristic of the price to be predicted). This training follows the following steps:

- Initialization of the model,
- The forward propagation,
- Calculation of loss or error
- Backpropagation
- Weights update
- Model evaluation
- Refinement and adjustment of the parameters of said model
- Model production implementation

Architecture and mathematical modeling of our contribution: Our problem consists in predicting the selling cost of agricultural products from a set of variables such as price history , economic data such as GDP, geopolitical events, plantation areas and also the quantity of product from these plantations. Thus presented, we formulate this problem as a regression task, where the objective is to predict a continuous variable (the price).

Let $X = \{x_1, x_2, ..., x_n\}$ all entries.

Formally X = {old price, plantation area, quantity produced, economic data, etc. }.

Each x_i represents an observation (price of a raw material at a given time for example)

$Y = \{y_1, y_2, ..., y_n\}$ = set of corresponding outputs, where y_i is the price to predict .

Proposed Deep Agricultural Neural Network Architecture

Our Architecture is as follows: Figure 1

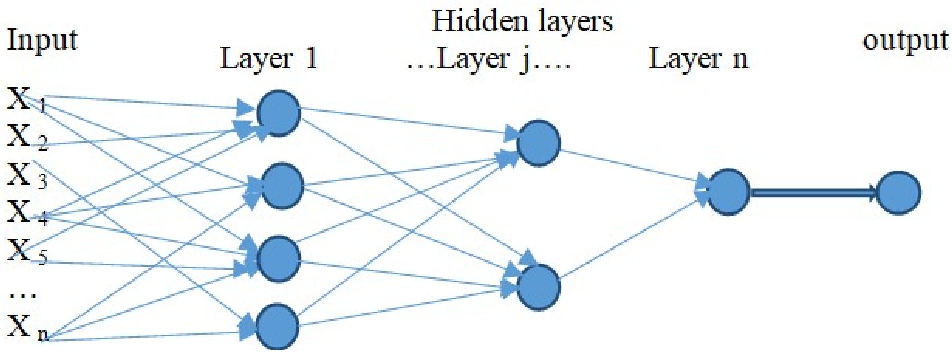

Figure 1. Architecture of the proposed neural network model

Our proposed architecture has three (3) components, which are:

The input component : it contains all the input values (area, old sales prices, currency fluctuations, age of plantations, quantities of herbicide or fungicide used, etc.) of our neuron. These values come from the villages, and production fields of the different agricultural products. This component is modeled by the set noted X = (x_1 , x_2 , x_3 ,… , x_n) which is a vector called the agricultural input vector of our neuron.

Hidden layers: These layers depend on previous layers (containing X data). Here, they could contain aggregated data (of departments, and districts) of production.

Let us denote by C = {c_1 , c_2, …, c_n} this set of intermediate hidden layers.

The output component: This layer constitutes the output of our neuron. It contains the predicted value, which is the selling price of the raw material at the national level. Let us denote $\hat{y}$this output .

Mathematical model of our agricultural neuron

For each neuron **j** in a layer, the output is given by equation (1)

$$z_j^{(l)} = \sum_{i=1}^{n} w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)} (1)$$

With$w_{ij}^{(l)} = \textit{is the weight}$(produced quantity)that links that input neural to the layer ,

this weight may be the production in tons

$a_i^{(l-1)} = \textit{be the output neural of the preceding layer}$ la ,
$b_j^{(l)} = \textit{the bias}$ neural of the layer .

Then, to the output described above, we apply a nonlinear activation function to $z_j^{(l)}$which we denote by **f** which is such that/

$$\boldsymbol{a_i^{(l-1)} = f\left(z_j^{(l)}\right) \quad (2).}$$

This activation function will allow our network to learn and adapt to complex agricultural data (ambient temperature in plantations, rainfall rate).

To have a better prediction, we present in Table 3 the different necessary activation functions. From this presentation, we make a choice with regard to the nature of the data processed.

Table 3. Presentation of the different activation functions

Function	Formula	Use
ReLU (Rectified Linear Unit):	f(x) = max(0, x)	Often used in hidden layers for its ability to handle positive values while avoiding the zero gradient problem.
Tanh (Hyperbolic Tangent):	f(x) =$\frac{e^x-e^{-x}}{e^x+e^{-x}}$	Used in hidden layers, it returns values between -1 and 1, which can help center the data
Sigmoid:	f(x) =$\frac{1}{1+e^{-x}}$	Less common for hidden layers, but can be used in situations where values need to be between 0 and 1. Not ideal for pricing, as it limits the output.
Linear:	f(x) =x	Ideal for the output layer in a regression model where the price can take any real value. This allows the model to predict prices outside the range [0, 1] or [-1, 1].

Choosing our activation function

So presented, we use in our case the following:

- *at the hidden layer level*, we use ReLU **(** because of its ability to generate positive values), the price to be predicted always being a positive value
- *At the output layer* , we also use a linear activation function because the price to be predicted can take any value (positive or negative). In our case it is a positive value

Cost function of our model

Since our problem falls within the domain of linear regression such as price prediction, our cost function (which is the mean square error (MSE)) is defined as follows:

Let us denote this function by J ; $\mathrm{J}(\emptyset) = \frac{1}{m}\sum_{i=1}^{m}(\hat{y} - yi)^2$(3) with:

- m is the total number of data in the set on which our model is trained,
- $\hat{y}$is the prediction (predicted price) of the model,
- $yi$is the real value of a sale price,
- $\emptyset$ Represents the network parameters (in our case the areas, the quantities produced, the quantities of herbicide and fungicide and the biases).

Prediction optimization step.

To optimize its price prediction, our agricultural neural network model adjusts its weights and biases through an optimization process, typically via gradient descent or its variants like **Adam or RMSprop** . Indeed, gradient descent updates the parameters in the opposite direction to the gradient of the cost function with respect to the parameters. Thus, this optimization phase is ensured by equation (4)

$\theta^{(t+1)} = \theta^{(t)} - \eta\frac{\partial J(\theta)}{\partial \theta}$(4)

With$\eta = \ learning\ rate$,

$\frac{\partial J(\theta)}{\partial \theta} = the\ gradient\ of\ cost\ function\ over$ parameters.

After the optimization phase, we train our model on data allowing to minimize the cost function $J(\emptyset)$and by adjusting the weights and biases during several iterations.

Also, to know if our model is performing, we use metrics like RMSE

(Root Mean Squared Error) or MAE (Mean Absolute Error) . These 2 metrics are presented as follows:

RMSE = $\sqrt{\frac{1}{m}\sum_{i=1}^{m}(\hat{y} - yi)^2}$ (5),

MAE = $\frac{1}{m}\sum_{i=1}^{m}|\hat{y} - yi|$ (6)

Proposed pseudo code: In this part, we propose a pseudo code to define the different tasks that intervene in the prediction process. They go from task 1 to task 8.

Task No. Task label	Pseudo code and explanation
1 - The pseudo code takes into account the handling of missing data and the normalization of variables. Normalization is essential so that the variables have a similar scale, facilitating the training of the model	

Data Preparation	**START**
	// Load basic data
	LOAD " dataset " with the following columns:
	- Historical prices of raw materials
	- Economic variables (inflation, interest rates, etc.)
	- Geopolitical variables (sanctions, conflicts, etc.)
	- Target selling price (to be predicted)
	// Check for missing values
	FOR each row in dataset
	IF missing values THEN
	IMPUTE missing values OR **DELETE** rows
	END IF

	END FOR *// Separate the explanatory variables (X) and the target variable (y)* X = dataset EXCLUDING the "target sales price" column y = dataset 'target sales price' *// Normalize the input data to put all variables on the same scale* INITIALIZE a normalizer X_normalized = NORMALIZE(X)
2 - The dataset is divided into training and testing sets to evaluate the performance of the model on unseen data	
Data Division	*// Split the data into training set and test set* **DIVIDE** X_normalized and y in training set (80%) and test set (20%) X_train , X_test , y_train , y_test = train_test_split (X_normalized , y, ratio=0.8)
3 - The neural network model is composed of multiple hidden layers with ReLU activation to introduce non-linearity, which helps to capture complex relationships in the data	
Construction of the Deep Neural Network	*// Initialize the neural network model* **INITIALIZE** deep neural network (DNN) model *// Add a first input and hidden layer* **ADD** layer with neurons = 64, activation = ReLU , input_dim = number of features in X_train *// Add a second hidden layer* **ADD** layer with neurons = 32, activation = ReLU *// Add a third hidden layer* **ADD** layer with neurons = 16, activation = ReLU *// Add an output layer with 1 neuron for continuous prediction* **ADD** layer with neurons = 1 (output layer), activation = linear
4 - The model is compiled with an MSE cost function (fits well to a regression problem). The training process adjusts the model weights using the Adam optimizer	
Model Compilation	*// Compile the model with a suitable cost function and an optimizer* **COMPILE** the model - loss function = Mean Square Error (MSE) for regression - optimizer = Adam - metric = MSE to evaluate performance
5 - The model performance is evaluated using the MSE (Mean Squared Error) and MAE (Mean Absolute Error), which are standard metrics for regression tasks	
Model Training	*// Train the model on the training data* **TRAIN** model with data (X_train , y_train) - epochs = 100 - batch_size = 32 - validation_split = 20% (to validate performance during training) *// Monitor error curves (loss) during training to avoid overfitting* **SHOW** the training and validation loss evolution curve
6 - After training, the model can be used to predict future commodity prices based on new economic and geopolitical variables.	
Model Evaluation	**PREDICT** Commodity Prices with X_test *// Calculate the mean square error (MSE) between the predictions and the actual values* **test_mse** = CALCULATE MSE(y_test , y_pred_test) *// Calculate the mean absolute error (MAE)* **test_mae** = CALCULATE MAE(y_test , y_pred_test) *// Show model performance* **DISPLAY** test_mse , test_mae
7 - The model can be regularly retrained if new data becomes available, ensuring always up-to-date predictions	
Use for Prediction on New Data	*// Load the new data for which we want to predict the cost of raw materials* **LOAD** new economic and geopolitical data *// Apply normalization to this new data* **new_data_normalized** = NORMALIZE(new_data) *// Use the trained model to predict future prices* **price_predicts** = PREDICT with model, new_data_normalized *// Show final predictions* **DISPLAY** price_predicts

8 - Model Update Loop (Optional)	*// If new data arrives regularly*
	WHILE new data is available DO
	ADD new data to dataset
	NORMALIZE new data
	RE-TRAIN the model with the new data
	END WHILE

Simulation: To validate our neural network model, we perform our simulation using a dataset comprising 10,000 records including climate variables, historical price data and characteristics of the kola nut harvest.

Data used

The input variables of our neural network are:

- Seasonal variables **(** Spring, Summer, Fall, Winter)
- Climatic variables (Average temperature (°C), Precipitation (mm)),
- Cultivated agricultural area (hectares)
- Price History (/ton)

Data produced

Predicted Price (/ton): The following table shows average values of 4 seasons for kola nut cultivation. After simulating our neural network on 10,000 seasonal data, we obtain Table **4**

Table 4. Presentation of average price predictions by season

Season	Temperature average	Precipitation (in mm)	Area (ha) average	Average historical price (/ton)	Average predicted price (/ton)
Summer	25	100	75	160	170
Autumn	10	150	60	155	165
Spring	15	200	50	150	160
Winter	5	300	30	140	155

Programming environment: The simulation of our neural network model was done in the Google colaboratory environment which is a programming platform supporting the python language.

Architecture of our Model

Network structure:

Our network is made up of:

- 4 hidden layers with 64 neurons per layer.
- Activation function: ReLU for hidden layers, and linear for the output layer.

Hyper parameters

- Learning rate : 0.001
- Batch size : 64
- Loss function : MSE (Mean Squared Error)

Model Performance: Regarding the performance of our model, we present it through Figure 2.

Prediction graph: Comparison between actual and predicted values for the 10,000 records. In this graph the predicted average values are in blue color and the old average values are in orange color

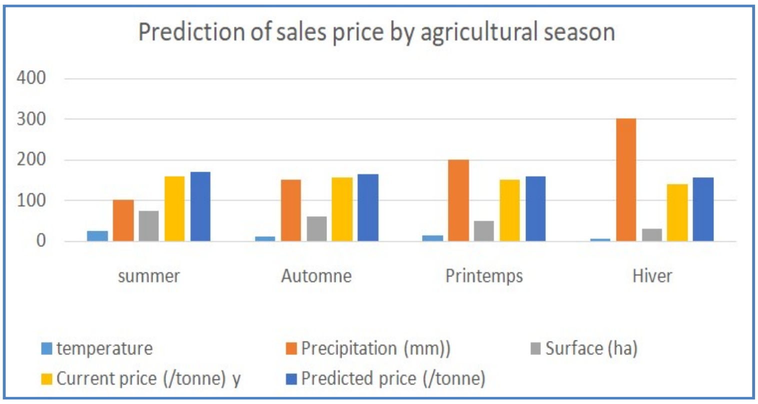

Figure 2. Presentation of price predictions by season

Performance metrics: For the performance measurement of our models, the differents parameters give the following values:

- **RMSE** : 8.75 / tonne
- **R²** : 0.94
- **MAE** : 5.50 / tonne

DISCUSSION

In this work, our objective was to propose a tool to help predict the selling prices of agricultural raw materials in order to contribute to the determination of the selling prices of agricultural products. The tool we proposed is a recurrent neural network applied to the data. After training our model on a set of agricultural data records (cola nuts), the model can be used to make predictions on new input data of other agricultural products.

This training allows the network (having an architecture modeled on the agricultural administrative organization of certain states) to predict the price of the desired product. In order to maintain its performance, the model can be updated with new data to take into account changes in the agricultural commodity market. Its performance is measured by the parameters RMSE, MAE and the correlation coefficient R^2. The results of these measurements show that neural networks can contribute to value prediction in the field of agriculture.

CONCLUSION

The objective of this work was to propose a method for predicting the sale prices of agricultural raw materials. To do this, we conducted a literature survey and presented the types of neural networks. Our proposal is inspired by existing artificial neural network models in that in choosing the activation function, we use the ReLU (Rectified Linear Unit) for the hidden layers of our model and linear regression in its output layer. These choices are justified by the fact that ReLU best processes positive data such as old prices, areas, etc. which constitute data processed by the intermediate layers of the network. In our proposal, an architecture and pseudo code to give intelligence to this architecture are proposed. The simulations of our model were carried out in a python environment with the Framework (Google colabotory). The results presented show that our model could be used by different institutions in their attempts to predict the prices of several raw materials. Our future work in the fields of agricultural value prediction could focus on the quantities produced based on the areas and inputs made available to producers. Also, prediction techniques could focus on predicting school and university results in our developing countries. This prediction would help the different states and institutions to better plan their development.

REFERENCES

Azencott, CA 2022. *Introduction to Machine Learning-2nd ed* . Dunod . Page 81

Bellahmer , H. 2020. *Implementation and evaluation of a machine learning model for estimating the market value of real estate properties* Doctoral dissertation, Mouloud Mammeri University.

Fatima, H., & Amina, S. 2023. *Time Series Prediction Using a Deep Learning Model Case Study: Sonelgaz* Doctoral dissertation, UNIVERSITY BBA.

Khelouat , I., & Mouali , K. 2020. *Anticipation of the value of cryptocurrencies using machine learning* Doctoral dissertation, Mouloud Mammeri University.

Hala, YT, & Yakine, HAMIMID 2023. *Oil price prediction using ARMA and ARIMA analytical methods* Doctoral dissertation, UNIVERSITY BBA.

Fiordaliso, A. 1997. An application of MLP artificial neural networks to the prediction of the price of a tradable option. *Economics & Forecasting* , *127* 1, 47-62.

Hachaichi, Y., & Abdennebi , MAB Study of market efficiency using recurrent neural networks.

Sleiman , R. 2022. *Trend detection and demand forecasting for fashion items using big data and artificial intelligence* Doctoral dissertation, Centrale Lille Institut.

BENMANSOUR, A., BOUZOUINA, SS, & OUDINAT, SH 2017. *Artificial intelligence assistance in decision-making* Doctoral dissertation.

Benmansour, A., Bouzouina, SS, & Oudinat, SH 2017. *Artificial intelligence assistance in decision-making* Doctoral dissertation.

Soukeur , EHIEI 2022. *Multi-objective artificial neural networks* Doctoral dissertation.

Belaid , MS 2022. *Modeling supply chain forecasting processes for improving industrial performance* Doctoral dissertation, Ecole nationale supérieure Mines-Télécom Lille Douai.

Salvail , A. ON THE USE OF DEEP LEARNING FOR PROBABILISTIC FORECASTING IN TIME SERIES.

Sarr , JMA 2023. *Study of data augmentation for the robustness of deep neural networks* Doctoral dissertation, Sorbonne University; Cheikh Anta University Diop Dakar.

Amel, HM, & Rania, ABDERRAHMANI 2021. *Implementation of a Deep Learning model based on a neural network on the STM32 card* Doctoral dissertation, UMMTO.

Ly, A. 2019. Machine *learning algorithms in insurance: solvency, textmining , anonymization and transparency* Doctoral dissertation, Université Paris-Est.

Sibaud, C., & Patissier, C. 2023. Chapter I. Online sales and artificial intelligence, a soon-to-be inseparable couple. *Hors collection* , 15-36.

MAHBOUB, S., & GUERBAZ, R. 2024. Comparative analysis between ARIMA models and artificial neural networks for stock price prediction. International Researcher's Review, 52.

****