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A Comprehensive Approach to Improving Enterprise Management Processes Through Applying Deep Learning Algorithms: A Case Study

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Abstract: ***This paper addresses the critical need to enhance the management of pension payments at Benin's National Social Security Fund (NSSF), highlighting the pivotal role of deep learning methodologies in achieving optimization. As a key institution responsible for safeguarding the financial well-being of the population through social security programs, the NSSF faces unique challenges in managing the large volume of regular pension payments. This study presents an innovative deep learning-based approach specifically designed to address the complexities of pension payment management at the NSSF in Benin. By leveraging advanced neural network architectures, our methodology aims to streamline and optimise the processes involved in pension disbursements, with a focus on enhancing accuracy, efficiency, and overall operational effectiveness. Key components of this approach include analysing historical pension payment data, demographic trends, and relevant socioeconomic indicators to develop predictive models that inform policy decisions. These models help forecast and adapt to changing patterns, ensuring timely and accurate pension payments. Through a detailed case study on the NSSF of Benin, we demonstrate the practical application of deep learning in addressing the specific challenges faced by public entities managing pension payments.***

Keywords: Deep Learning, Pension Payment Management, National Social Security Fund, Optimization.

I. INTRODUCTION

The National Social Security Fund (NSSF) of Benin stands as a cornerstone in the nation's commitment to ensuring the financial well-being and security of its citizens through comprehensive social security programs. Among the many responsibilities shouldered by the NSSF, the management of pension payments stands out as a critical and complex task, involving the disbursement of funds to a diverse and growing population at regular intervals. Given this complexity, applying advanced technologies is imperative to streamline processes, enhance efficiency, and ensure the sustainability of pension systems.

This paper undertakes a pioneering exploration of the use of deep learning as a catalyst for optimising pension payment management, with a particular focus on the context of the National Social Security Fund of Benin. By introducing a deep learning-based approach, we aim to address the unique challenges inherent in managing a substantial volume of periodic pension payments while navigating the dynamic landscape of demographic shifts, economic fluctuations, and regulatory changes.

The importance of efficient pension payment management cannot be overstated, considering its direct impact on the livelihoods of retirees who depend on these funds for financial stability. The intersection of technological innovation and public financial management presents an opportunity not only to streamline processes but also to enhance the accuracy and reliability of pension disbursements. Various authors propose the use of machine learning to predict financial crises. Liu et al [1], Marhwal et al. and Jain et al. suggest that machine learning methods should be used when establishing early warning systems to predict financial crises in the future. Katib et al [4]., propose a hybrid hunter–prey optimization with the deep learning-based FCP (HHPODL-FCP) technique which uses the HHPO algorithm for the feature subset selection process. Their objective is to predict financial crises in the financial technology sector. Wang and Zong [5] demonstrate that machine learning outperforms canonical models in alarming crises. They also indicate that the private sector can benefit from ML-based EWS in the short term. Casabianca et al [6]. Used a machine learning approach, namely AdaBoost, to rank the determinants of banking crises over time and across countries. Their work covers a total of 100 countries, advanced and emerging, over the years from 1970 to 2017. Several research works have also been conducted to incorporate machine learning. In this direction, Samitas et al. suggested using neural networks [7]. A global literature review was presented by Henrique et al [8]. The use of deep learning as a machine learning method continues to advance [9, 3]. Shinde and Shah [2] present a review of machine learning and deep learning applications.

In this paper, we propose a deep learning-based approach to managing a public entity. The significant contribution of this article lies in the introduction and application of deep learning to optimize pension payment management at the National Social Security Fund (NSSF) of Benin.

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The key contributions are summarized as follows:

1. Innovative Methodology: The paper introduces a pioneering methodology that leverages deep learning techniques, specifically advanced neural network models, to analyze historical pension payment data, demographic trends, and socioeconomic indicators. This innovative approach surpasses traditional methods, providing a data-driven and adaptive solution to the complex challenges of managing a substantial volume of periodic pension disbursements.
2. Improved Accuracy and Efficiency: By applying deep learning algorithms, the study aims to enhance the accuracy and efficiency of pension payment processes. The developed models can learn and adapt to evolving patterns, resulting in more precise predictions of future pension payment requirements. This contributes to reducing errors, delays, and uncertainties in the disbursement process, ultimately benefiting retirees and ensuring a more reliable financial support system.
3. Risk Identification and Mitigation: The integration of deep learning algorithms for risk assessment represents a critical contribution to the financial stability of the NSSF. The paper addresses the identification and mitigation of potential risks associated with pension payment management, providing a proactive approach to safeguarding the fund against adverse economic conditions, regulatory changes, or other factors that may impact the reliability of pension disbursements.
4. Practical Application in a Real-world Setting: The case study on the National Social Security Fund of Benin serves as a tangible demonstration of the proposed methodology. The practical application of deep learning in a public entity managing pension payments provides valuable insights for policymakers, fund administrators, and stakeholders. It illustrates the feasibility and benefits of incorporating advanced technologies into the financial management of social security institutions.
5. Contribution to the Intersection of Technology and Public Financial Management: This research contributes to the broader discourse on the intersection of technology, intense learning, and public financial management. By addressing the specific challenges faced by social security institutions in managing pension payments, the paper opens avenues for further exploration and discussion on the role of artificial intelligence in optimizing financial systems within the public sector.

The rest of our article is organized as follows. The second section presents the materials. The third section presents the methods. In the fourth section, we present our results. Finally, we end the paper with a conclusion.

II. MATERIALS

A. Dataset

As with all machine learning problems, the training and evaluation of a model are conducted using a set of examples or observations referred to as a dataset. Data plays a crucial role in achieving the objectives of this work. To this end, we opted to extract data from the pension database of the National Social Security Fund (NSSF). Specifically, we extracted and anonymized the data of deceased pensioners to create a test dataset. Initially, we obtained just under 30,000 records. It was then necessary to extract data from the pension holders and cross-reference them with pension payments to accurately determine the last payment date. Ultimately, we finalised a test dataset comprising 25,835 records.

For each record, we have the following information:

- **type_pens**: pension category (normal pension, early pension, disability);
- **country code**: country of the pensioner;
- **pension**: the pension amount;
- **withholding**: withholding from the pension;
- **retirement CNSS**: type of pensioner;
- **nb_enf**: number of minor children.

Nominal type attributes (pension category, pensioner type) have been transformed into numeric type.

B. Development Environment

All our experiments were carried out on a computer with the following characteristics:

- Operating system: Windows 10
- Architecture: 64 bits
- Processor: Intel(R) Pentium(R) CPU 4415U @ 2.30GHz 2.30 GHz
- RAM: 8.00 GB

The algorithms were implemented using Python with the Scikit-learn library.

III. METHOD

In our work, we propose the prediction (quantification) of the duration of pension payments to a pensioner. The methodology we used in our study is similar to that employed in classic classification and regression problems. The process is illustrated in Figure 1.

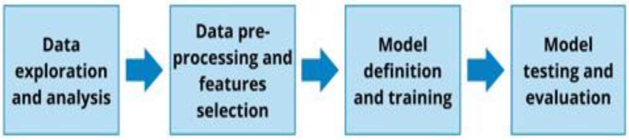

Fig. 1: Steps of our Methodology

A. Data Exploration and Analysis

This is the first step of our method. It involves exploring and analysing the data to gain a thorough understanding and making observations that can guide the actions to be taken in the subsequent steps. Thus, we determine the size of the dataset, its various characteristics, the types of data, and the presence of missing values. The objective of data exploration and analysis in machine learning is to gain a deep understanding of the dataset before building and training a model. This phase is crucial for making informed decisions regarding data preprocessing, feature engineering, and selecting an appropriate machine learning algorithm.

B. Data Pre-Processing and Feature Selection

The objective of this step is to transform the dataset into an optimised format that is conducive to machine learning algorithms.

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This is the step that has the most significant impact on model performance. So, we have undertaken specific actions, which are in particular:

- **Handling Missing Values**: Most deep learning algorithms require that all data be present and digital. We differentiate the missing values by the values entered by replacing them with -1 (which is a value different from all values in our dataset). This method works better than replacing missing values with the value zero for numerical (quantitative) variables and with the 'missing' category for categorical (qualitative) variables because these missing values have a different meaning and represent actual values.
- **Encoding of Categorical (Qualitative) Variables**: This involves transforming the values of categorical variables into digital values.

Normalisation of Variables: It's about putting the values on the same scale. This is important because in some deep learning algorithms, the objective functions do not work correctly, and the gradient descent does not converge quickly without normalisation. We use the standard normalization defined by the equation where x is the value to transform, $\bar{x}$ the mean of the variable, σ its standard deviation, and x′ the new value: $x' = \frac{x - \bar{x}}{\sigma}$.

C. Model Definition and Training

Once the data is preprocessed and optimized, it can be used to train different classification and regression models. We utilised the Scikit-learn library to split our dataset into training and testing sets. This is necessary so that we can use part of the pensioners' data to train the model and another part to test its performance. Splitting a dataset in this way is a common practice when building deep learning models. It is essential to implement this split in the dataset so that the model we create does not have access to the test data during the training process. This ensures that the model learns only from the training data, allowing us to then test its performance with the test data. If we expose our model to test data during the training process, it will learn to produce the expected results. Therefore, it would not give accurate predictions on data it has not seen. For the creation of our learning model, we specified four layers:

- an input layer to which we transmitted the entities of our dataset;
- two (02) hidden layers, which were used to carry out the treatments;
- an output layer that gives the results after training our model

D. Model Testing and Evaluation

Once the model was designed, we conducted tests using the data. We used 24252 for training and 1583 for testing. The importance of this part lies in verifying the robustness of the designed model.

IV. RESULTS AND DISCUSSIONS

Our test dataset comprises 1,583 samples of pension payments, aggregated by year. Seven (07) basic characteristics describe each sample in addition to the variable to be predicted, which is "duration", which designates the number of years during which the National Social Security Fund of Benin will continue to pay the pension to the insured. Figure 2 presents the description of the test dataset, whereas Figure 3 shows the definition and training of our model. The model, once established, enables us to conduct tests and compare the values obtained with the target values. This manipulation aims to verify whether the designed model enables the reliable estimation of values.

The results are presented in Figure 4. We observe that our model can capture general trends, but sometimes yields results that deviate significantly from the actual values. We observe that our model can capture general trends, but sometimes yields results that deviate considerably from the actual values.

We finally proceeded to evaluate our model. The metric used for the evaluation is the square root of the mean square error. It is the square root of the mean of the squared differences between the forecast and the actual observation. It allows you to evaluate the overall error of a prediction. The formula gives the calculation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}}$$

In this formula, n represents the size of the sample on which the prediction is made, y_i is the real value for the i-th element in the sample, and ŷ is the predicted value for this element. The performance results (RMSE) of our model are presented in Figure 5.

V. CONCLUSION

This paper has explored the potential of deep learning as a transformative tool for optimizing the management of pension payments at the National Social Security Fund of Benin. The unique challenges associated with handling a significant volume of periodic pension disbursements demand innovative solutions, and our deep learning-based approach provides a promising avenue for improvement. Through the application of advanced neural network models, we have demonstrated the capacity to analyze historical pension payment data, demographic trends, and socioeconomic indicators. This analysis enables the development of accurate predictive models that enhance the fund's ability to forecast and adapt to evolving patterns in pension disbursements.

```
Entrée [2]: df = pd.read_csv('./data_deep_learning/pensionnes.csv', sep = ';')
            print(df.shape)
            df.describe()

            (1583, 7)
Out[2]:
```

	type_pension	code_pays	pension	retraite_cnss	retenue	nb_enf	duree
count	1583.000000	1583.000000	1.583000e+03	1583.000000	1583.000000	1583.000000	1583.000000
mean	1.170562	1.026532	1.390817e+05	0.022110	3867.384713	1.128238	2.999368
std	0.426633	0.298422	2.334135e+05	0.147088	16177.153724	1.666387	1.739516
min	1.000000	1.000000	1.985000e+03	0.000000	0.000000	0.000000	1.000000
25%	1.000000	1.000000	2.725000e+04	0.000000	0.000000	0.000000	2.000000
50%	1.000000	1.000000	6.070000e+04	0.000000	0.000000	0.000000	2.000000
75%	1.000000	1.000000	1.576000e+05	0.000000	0.000000	2.000000	4.000000
max	3.000000	6.000000	5.328800e+06	1.000000	322066.000000	6.000000	10.000000

Fig. 2: Description of the Test Dataset

```
# Define model
model = Sequential()
model.add(Dense(500, input_dim=6, activation= "relu"))
model.add(Dense(100, activation= "relu"))
model.add(Dense(50, activation= "relu"))
model.add(Dense(1))
#model.summary() #Print model Summary
```

```
model.compile(loss= "mean_squared_error" , optimizer="adam", metrics=["mean_squared_error"])
model.fit(X_train, y_train, epochs=20)
```

```
Epoch 1/20
35/35 [==============================] - 0s 5ms/step - loss: 5.8400 - mean_squared_error: 5.8400
Epoch 2/20
35/35 [==============================] - 0s 5ms/step - loss: 2.7577 - mean_squared_error: 2.7577
Epoch 3/20
35/35 [==============================] - 0s 4ms/step - loss: 2.1440 - mean_squared_error: 2.1440
Epoch 4/20
35/35 [==============================] - 0s 4ms/step - loss: 1.2925 - mean_squared_error: 1.2925
Epoch 5/20
35/35 [==============================] - 0s 4ms/step - loss: 0.6763 - mean_squared_error: 0.6763
Epoch 6/20
35/35 [==============================] - 0s 4ms/step - loss: 0.6016 - mean_squared_error: 0.6016
Epoch 7/20
35/35 [==============================] - 0s 4ms/step - loss: 0.5669 - mean_squared_error: 0.5669
Epoch 8/20
35/35 [==============================] - 0s 5ms/step - loss: 0.5541 - mean_squared_error: 0.5541
Epoch 9/20
35/35 [==============================] - 0s 5ms/step - loss: 0.5145 - mean_squared_error: 0.5145
Epoch 10/20
35/35 [==============================] - 0s 4ms/step - loss: 0.5129 - mean_squared_error: 0.5129
Epoch 11/20
35/35 [==============================] - 0s 4ms/step - loss: 0.5154 - mean_squared_error: 0.5154
```

Fig. 3: Model Definition and Training

```
Entrée [10]: import matplotlib.pyplot as plt

Entrée [22]: plt.figure(figsize = (14,5))
             plt.plot(y_test, color = 'red', label = 'Duree Reelle de Paiement des Pensions')
             plt.plot(pred, color = 'blue', label = 'Duree de Paiement des Pensions Predites')
             plt.title('Prediction de la duree de paiement des pensions')
             plt.xlabel('ID Pensionnes')
             plt.ylabel('Duree')
             plt.legend()
             plt.show()
```

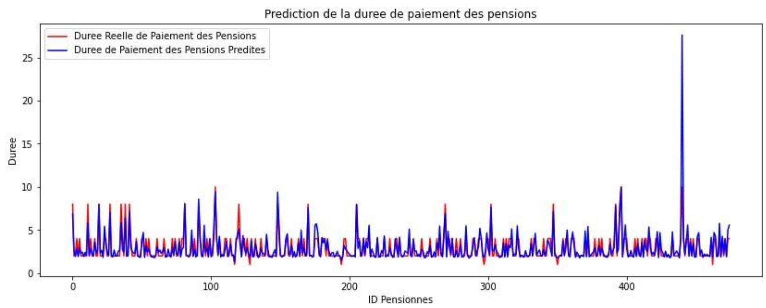

Fig. 4: Comparison Between Actual Data and Predicted Data

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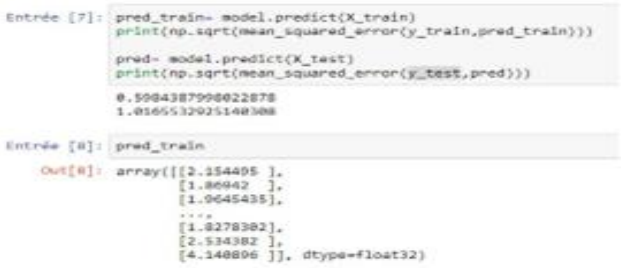

```
Entrée [7]: pred_train= model.predict(X_train)
            print(np.sqrt(mean_squared_error(y_train,pred_train)))

            pred= model.predict(X_test)
            print(np.sqrt(mean_squared_error(y_test,pred)))

            0.5984387998022878
            1.0165532925140308

Entrée [8]: pred_train

Out[8]:     array([[2.154495 ],
                   [1.86942  ],
                   [1.9645435],
                   ...,
                   [1.8278382],
                   [2.534382 ],
                   [4.148896 ]], dtype=float32)
```

Fig. 5: Performance Evaluation

The integration of deep learning algorithms for risk identification and mitigation further contributes to the financial stability and reliability of the pension payment system.

The case study on the NSSF of Benin serves as a practical illustration of the benefits and feasibility of implementing deep learning in the context of public entities managing pension payments. The positive impact on accuracy, efficiency, and operational effectiveness is evident, highlighting the potential for broader applications within the field of financial management for social security institutions.

In conclusion, this research contributes to the growing body of knowledge on the intersection of deep learning and public financial management, providing insights that can inform future advancements in optimising pension payment systems. The outcomes of this study underscore the importance of embracing technological innovations to address the evolving needs of social security institutions, ultimately contributing to the financial well-being and security of the population in Benin and beyond.

DECLARATION STATEMENT

I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it was conducted without any external influence.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed solely.

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Dr. Mikaël A. Mousse has been a faculty member at the University of Parakou since December 2018, where he serves as a lecturer and researcher. His research interests are focused on cutting-edge technologies, including computer vision, multimedia information retrieval, cryptography, blockchain, and artificial intelligence systems. Our work aims to propose computer models to solve the problems facing society.