Innovative Applications of Artificial Neural Networks in Tax Forecasting

Aplicações inovadoras de redes neurais artificiais na previsão fiscal

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ABSTRACT

The importance of forecasting tax revenues is vital for economic planning and financial sustainability in Mozambique. This study addresses this topic by exploring the potential of Artificial Neural Networks (ANNs) to improve such forecasts. The central problem is the limitation of conventional methods in capturing the complexity of tax data. The rationale for adopting ANNs lies in their superior modeling and forecasting capacity in large and complex data environments. The results obtained demonstrate that ANNs can forecast tax revenues with greater accuracy, outperforming traditional models. The conclusion points to ANNs as a valuable tool for tax authorities, increasing collection efficiency and contributing to the country's fiscal stability.
Keywords: neural networks; tax forecast; Sustainability

RESUMO

A importância da previsão das receitas fiscais é vital para o planeamento econômico e sustentabilidade financeira em Moçambique. Este estudo aborda este tópico explorando o potencial das Redes Neurais Artificiais (RNAs) para melhorar tais previsões. O problema central é a limitação dos métodos convencionais em captar a complexidade dos dados fiscais. A razão para a adoção de RNAs reside na sua superior capacidade de modelação e previsão em ambientes de dados grandes e complexos. Os resultados obtidos demonstram que as RNAs podem prever as receitas fiscais com maior precisão, superando os modelos tradicionais. A conclusão aponta para a RNA como uma ferramenta valiosa para as autoridades fiscais, aumentando a eficiência na cobrança e contribuindo para a estabilidade fiscal do país.
Palavras-chave: redes neuronais; previsão fiscal; sustentabilidade.

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1 INTRODUCTION

Responsible tax management forms the foundation for a nation's economic growth and stability (Bartoluzzio & Anjos, 2020). In Mozambique, where sustainable development is a priority, accurate forecasting of tax revenues plays a critical role. Tax authorities face the continuing challenge of estimating revenue effectively, a task complicated by economic volatility and a constantly evolving fiscal environment. In this scenario, technology emerges as a potential ally, and Artificial Neural Networks (ANNs) represent an innovative frontier in predictive analysis.

The ability to accurately predict tax revenues is an essential component in the administration of any modern economy (da Silva et al., 2020). For Mozambique, a country seeking to strengthen its fiscal infrastructure and promote economic development, the adoption of advanced technologies such as ANNs can be a divider. The complexity of today's economic systems requires tools that can learn and adapt to dynamic patterns, an area where ANNs excel. By integrating historical data with contemporary economic variables, ANNs offer an opportunity to anticipate fiscal trends with unprecedented accuracy.

Furthermore, the topic of ANNs in the fiscal forecast is relevant for Mozambique due to its emerging economy and the need to optimize the collection of revenues (Lima & Bezerra, 2022). Accurate tax forecasting is not only a matter of administrative efficiency but also one of social justice (da Silva et al., 2020). Reliable revenue forecasts enable the government to allocate resources more effectively, ensuring the provision of essential public services and facilitating investment in critical areas (Bartoluzzio & Anjos, 2020). Therefore, the use of ANNs to improve fiscal forecasts represents an initiative with the potential for a profound and lasting impact on the country's economic and social well-being.

The question that arises is: how can ANNs be applied to improve the accuracy of tax collection forecasts in Mozambique? This issue arises in a context where traditional forecasting methods often fail to capture the complexity and dynamics of tax data. The objective of this study is to investigate the applicability of ANNs in analysing historical data and economic factors, to improve the accuracy of future revenue forecasts.

The justification for exploring this topic is compelling. Accurate forecasts are vital for tax planning and resource allocation, directly impacting the government's ability to finance public services and invest in infrastructure. Furthermore, the reliability of tax estimates is crucial for maintaining the confidence of both investors and citizens.

The importance of this study for Mozambique cannot be overstated. By adopting ANNs in fiscal forecasting, the country can make a significant leap in its economic management capabilities. This approach not only strengthens tax collection but also promotes more transparent and efficient governance, which is essential for socio-economic progress and the realization of a long-term vision for national development.

2 DISCUSSION OF TOPICS

2.1 Neural Networks Modelling and Performance

ANN modelling is a key component in forecasting tax revenues, especially in complex economic contexts such as Mozambique. Developing an ANN model involves carefully selecting the network architecture, including the number of hidden layers and neurons, which must be adequate to capture data complexity without leading to "overfitting" (Almeida et al., 2020). The initial configuration of weights and "biases", along with the selection of appropriate activation functions, are critical decisions that impact the network's learning efficiency (Araújo 2022).

ANN training is an iterative process in which weights are adjusted to minimize prediction error (dos Santos Neto, et al., 2020). This adjustment is achieved through optimization algorithms, such as the descending gradient, which modify the weights in response to the observed error between the network's forecasts and actual values. During training, it is essential for the model not only to learn the patterns in the training data but also to generalize well to unseen data, a quality verified through a validation set (Nascentes, 2020).

In the literature, we can also cite the work of Simon Haykin (1999), especially his book "Neural Networks: A Comprehensive Foundation", which thoroughly addresses the modelling and performance of artificial neural networks. Haykin explores the mathematical and theoretical underpinnings of neural networks, providing essential insights into how these networks can be modelled and optimized for improved performance.

The performance of ANNs is assessed based on their accuracy and reliability in predictions (Announcement, 2023). Factors such as the quantity and quality of training data, the complexity of the model, and the adequacy of optimization techniques play significant roles in the effectiveness of predictions. In Mozambique, where data can be scarce or noisy, the robustness of the ANN model is important. Therefore, the modelling and performance of ANNs must be approached with a deep understanding of the specifics of tax data and the country's economic environment (Almeida et al., 2020).

The choice of training data is another factor that significantly influences the performance of ANNs. In Mozambique, selecting representative data is challenging due to economic variability and the limited availability of tax data. The quality of the data, including its completeness and accuracy, determines the ANN's ability to learn relevant patterns and make reliable predictions (Araújo, 2022). Therefore, data collection and pre-processing are fundamental steps that precede network training.

Cross-validation is a common technique used to evaluate the generalization of the ANN model. It involves splitting the data set into several parts, training the model on some of these parts, and validating it on the others. This method helps identify whether the model is overfitted to the training data and whether it can accurately predict previously unseen data (dos Santos Neto et al., 2020).

Furthermore, the ability of an ANN to handle unstructured and noisy data is particularly valuable in Mozambique, where data collection systems may be underdeveloped. ANNs can extract useful information from imperfect data, which offers a significant advantage over more traditional methods that require highly structured and clean data (Almeida et al., 2020). Finally, the interpretability of ANN models is a crucial factor, especially when applied to tax decisions that impact the population and economy of Mozambique. Highly complex ANN models can be difficult to interpret, raising concerns about the transparency and accountability of predictions. Therefore, it is important to consider not only the model's performance in terms of accuracy but also its ability to be explained and justified to stakeholders (Araújo, 2022).

2.2 Applications of ANNs in Financial Forecasts

ANNs have emerged as a powerful tool for predicting financial indicators, including stock market trends (de Oliveira & dos Santos, 2020). In Mozambique, where the economy faces complex challenges and financial data is highly volatile, ANNs offer an innovative approach to improving the accuracy of fiscal forecasts. Dornelles et al. (2022) highlight several applications, including:

Stock Price Forecast: ANNs have been successfully applied to predict stock prices, assess risks, and support investment decisions. A classic example is the study by Kimoto et al. (1990), in which Artificial Neural Networks were used to predict stock prices on the Tokyo Stock Exchange. These networks analyze historical price time series and incorporate information such as trading volume, past trends, and technical indicators to generate future forecasts.

Financial Time Series Models: ANNs can be adapted to model financial time series, including exchange rates, interest rates, inflation, and commodity prices. The work of Zhang et al. (1998) demonstrated the effectiveness of ANNs in modeling financial time series, such as predicting exchange rates. ANNs learn from past patterns and capture nonlinear relationships between variables. In Mozambique, where economic data may be scarce and noisy, ANNs offer an advantage in handling the complexity of these time series.

Overcoming Limitations of Traditional Models: ANNs overcome the limitations of traditional models, such as linear regression, which often fail to capture the nonlinear characteristics of financial data. Hutchinson et al. (1994) compared ANNs with traditional regression models in predicting option prices and demonstrated the superiority of ANNs. In the context of Mozambique’s growing economy and volatile markets, ANNs represent a valuable alternative for predicting fiscal trends with greater accuracy.

Challenges and Opportunities: The application of ANNs requires expertise in hyperparameter tuning and model adjustment. Furthermore, interpreting these models presents challenges, particularly in the context of tax-related decisions. Hornik et al. (1989) discuss the technical challenges associated with training ANNs, including the need for proper hyperparameter tuning to ensure model generalization. Despite these challenges, ANNs offer a promising approach to financial forecasting in Mozambique, contributing to more efficient and informed management.

A renowned study that can be cited here is Rosenblatt's foundational work (1958). Although the author focused on the development of the Perceptron, a precursor to modern neural networks, his research opened the door to diverse applications, including financial forecasting. The evolution of neural networks for complex tasks such as financial forecasting stems from Rosenblatt’s original concept that machines could learn and make predictions based on data (Rosenblatt, 1958).

De Oliveira and dos Santos (2020) report that the application of ANNs in financial forecasting is a field that is gaining increasing prominence, especially in emerging markets such as Mozambique. The ability of ANNs to process and learn from large volumes of data makes them suitable for analysing financial markets, which are characterized by their complexity and uncertainty.

Forecasting economic indicators, such as gross domestic product (GDP) and inflation, is another area where ANNs can be extremely useful. By incorporating a wide range of economic and social variables, ANNs can help identify trends and patterns that may not be immediately apparent to human analysts or through traditional statistical methods (Rodella, 2023).

In addition, ANNs can be applied to forecast tax revenues, a crucial aspect of economic governance. In Mozambique, where tax planning and resource allocation present significant challenges, ANNs can provide more accurate and reliable forecasts, enabling policymakers to make more informed decisions (Dornellas et al., 2022).

However, it is important to note that while ANNs offer many advantages, they also present challenges. The quality of input data is crucial to the success of forecasts. In countries such as Mozambique, where there may be restrictions on data collection and processing, it is essential to ensure that data is of high quality and representative of the economic reality (Rodella, 2023).

2.3 ANNs in Decision Support Systems

ANNs are transforming decision-making processes within organizations. By providing data-based predictions, ANNs enable managers and administrators to make more informed and strategic choices (Schuch, 2021). The accuracy of these predictions is crucial, as decisions based on inaccurate information can lead to unwanted results.

In decision support systems, ANNs analyse large volumes of data to identify patterns and trends that may not be obvious to humans. This is useful in complex and dynamic environments, where the amount of data can be overwhelming. ANNs help filter the noise and focus on the most relevant information (de Souza, et al., 2022).

The integration of ANNs into decision support systems is also beneficial in terms of efficiency (Bastos et al., 2019). By automating data analysis, ANNs reduce the need for manual analysis, which can be time-consuming and error-prone. This enables decision-makers to focus on interpreting results and planning actions rather than on data processing (Figueiredo, 2022).

A relevant study to cite here is the work of McCulloch and Pitts (1943), whose formal neuron model marked a milestone in understanding how the brain could be mathematically represented and simulated by machines. This concept is fundamental to neural network-based decision support systems, where networks process complex information to aid in decision-making (McCulloch & Pitts, 1943).

However, implementing ANNs in decision support systems presents certain challenges. One of the keys is to ensure that ANN models are transparent and explainable (Schuch, 2021). Decision-makers need to understand how predictions are made to trust them. Therefore, the interpretation of ANN models remains an active and critical area of research.

Another challenge is the need for high-quality data, as ANNs are only as effective as the data on which they are trained (de Souza, et al., 2022). In scenarios where the data is incomplete, inaccurate, or difficult, the predictions generated by ANNs can be questionable. Thus, data collection and pre-processing are vital steps in developing effective decision support systems (Figueiredo, 2022).

Furthermore, ANNs must be adapted to the specific context in which they are applied. This means that the models need to be customized to reflect the "nuances" of the decision-making environment. For example, in Mozambique, ANNs used in tax decision support systems must account for local economic factors and tax collection patterns (de Souza et al., 2022).

Collaboration between data experts and decision-makers is essential for the successful implementation of ANNs in decision support systems. Data experts can build and adjust ANN models, while decision-makers provide data about the needs and objectives of the organization. This collaboration ensures that ANNs are used effectively and aligned with organizational strategies (Schuch, 2021).

In this way, Fernandes (2020), describes steps that demonstrate the application of ANNs in decision support systems, such as:

- Data collection: Gathering data relevant to the decision problem;
- Data Processing: Cleaning and preparing of data for analysis;
- Definition of the ANN Model: Choosing the neural network architecture appropriate to the problem;
- ANN Training: Using the data to train the neural network model;
- ANN Validation: Testing the model with a separate dataset to ensure that it generalizes well for new data;
- Results Interpretation: Analysing the ANN outputs to understand the predictions or classifications made;
- Integration with the Decision System: Implementing the ANN as part of the decision support system;
- Decision making: using the information provided by the ANN to make informed decisions, and;
- Evaluation and Adjustment: Monitoring the performance of the decisions taken and adjusting the ANN model as necessary.

In conclusion, ANNs play a significant role in decision support systems. They hold the potential for more accurate predictions and more efficient decision-making processes. However, to integrate them effectively, challenges such as model interpretability, data quality, and context-specific customization must be addressed. Once these challenges are overcome, ANNs can become an invaluable tool for decision-makers in Mozambique and beyond.

2.4 Success cases with ANNs in Tax Forecast

The use of ANNs in fiscal forecasting has proven to be a promising approach in numerous case studies worldwide. For example, a study conducted in the state of Rio de Janeiro, Brazil, employed ANNs to predict the collection of the Tax on Circulation of Goods and Provision of Services (ICMS), one of the country's main taxes. The ANN model chosen was the Long Short-Term Memory (LSTM), which is suitable for time series due to its ability to remember information over extended periods (Figueiredo, 2022).

Again, the work of Rosenblatt (1958) is relevant here, as his Perceptron was one of the first models to demonstrate the ability of machines to perform predictive tasks. Applications of neural networks in specific areas, such as fiscal forecasting, are offshoots of the supervised learning concept he introduced.

Another case study in Rio Grande do Sul, Brazil, developed a short-term univariate model using LSTM ANNs to predict monthly ICMS revenue. The model showed a cumulative forecasting error of -2.33% in six one-step forecasts, demonstrating significant gains compared to other predictive methods previously used by the State Treasury Secretariat (Dornelles et al., 2022).

For the evaluation model, Dornelles et al. (2022) used the Mean Squared Error (MSE), as explained be$the\ \text{MSE} = \sum_{i-1}^{n}(\text{real} - \text{previson})^2$

n

These case studies illustrate how ANNs can be applied in tax revenue prediction, offering a more accurate and reliable alternative compared to traditional methods. Choosing the appropriate ANN architecture, such as LSTM, is crucial for capturing the dynamics and nonlinearities of fiscal time series (Rodella, 2023).

In the studies by Oliveira and dos Santos (2020) entitled "Strategies to Combat Tax Evasion: A Model for Artificial Neural Networks-Based ICMS", the authors discuss the development of an ANN model aimed at improving the prediction and detection of tax evasion related to the ICMS. This type of model could be useful for tax authorities, enabling them to identify evasion patterns and optimize audit and tax collection strategies. The application of ANNs in this context suggests an innovative and data-driven approach to addressing a significant tax problem, potentially leading to greater efficiency and fairness within the tax system.

Bastos et. al (2019), in their study entitled "Financial Validation of Neural Network Training Algorithms for Financial Series Trend Prediction", explore the application of ANNs for predicting trends in financial data. The authors investigated the effectiveness of different ANN training algorithms in financial time series, focusing on the validation and accuracy of predictions. Although the exact content of the study is not directly accessible, the research appears to be relevant for enhancing financial forecasting techniques and optimizing decision-making in economic contexts.

The implementation of ANNs in tax projections also requires a careful analysis of available data and a clear understanding of tax objectives. The quality of input data, the selection of relevant variables, and the definition of appropriate parameters are critical factors for the model's success (Rodella, 2023).

In addition, case studies highlight the importance of validating and testing ANN models. Using techniques such as cross-validation and comparison with "benchmarks", it is possible to assess the robustness and reliability of predictions generated by ANNs.

In short, case studies with ANNs in tax prediction provide valuable data on how these models can be adapted and optimized for different tax contexts. They also highlight the potential of ANNs to improve the accuracy of tax predictions, which is essential for effective financial planning and management.

2.5 Comparison with Traditional Methods

Artificial Neural Networks (ANNs) have been increasingly used in tax prediction, demonstrating their ability to model complex nonlinear relationships that traditional methods may not capture efficiently. Linear regression, for example, is limited by its assumption of linearity between variables (Bartoluzzio & Anjos, 2020). While time series and econometric models are useful, they may not adapt well to volatile or unstable data patterns (Peixoto et al., 2016).

In contrast, ANNs, with their flexible structure and learning ability, can identify hidden patterns in data, which is particularly valuable in tax prediction, where anomalies and unforeseen events are common. Studies such as Souza's (2011), which compared ANNs to traditional methods for predicting the BOVESPA index, demonstrate that ANNs can surpass traditional techniques in terms of accuracy.

In addition, ANNs can process an abundance of input variables without the need for pre-selection or transformation, unlike econometric models that often require variables to be carefully chosen and transformed (Araújo, 2020). This allows ANNs to capture complex interactions between variables that can be neglected in traditional methods.

Haykin (1998) addressed the comparison between neural networks and traditional methods of analysis and prediction in his work. He discussed the advantages of ANNs, particularly their flexibility and ability to handle nonlinear data, comparing them to more traditional techniques such as linear statistical models.

However, it is important to note that ANNs also have disadvantages. They can be opaque, making it difficult to interpret the results and understand how inputs influence forecasts. Additionally, ANNs require large datasets for training and may be prone to overfitting, particularly if not properly regularized (Almeida et al., 2020).

Empirical evidence suggests that ANNs offer significant improvements in terms of accuracy and reliability in tax predictions. For example, a dissertation from the Federal University of Rio Grande do Norte found that ANNs provided more accurate predictions of the BOVESPA index compared to time series methods (Souza, 2011). Another study by the Federal University of Itajubá highlighted the applicability of ANNs in forecasting economic indicators, surpassing traditional statistical models (Freiman, 2004).

However, the choice between ANNs and traditional methods should not be made in isolation. The decision must consider the specific context of the forecast, the availability of data, the need for interpretability, and the modeler’s experience. In some cases, a combination of methods may provide the most robust approach, taking advantage of the strengths of each method.

In short, while ANNs present clear advantages in terms of flexibility and modeling ability, they also require careful application to avoid pitfalls such as overfitting. The literature indicates that, when properly applied, ANNs can indeed offer substantial improvements over traditional methods. However, a thorough assessment of each specific situation is essential.

2.6 The Connection Between Neural Networks and Artificial Intelligence: The Role of Deep Learning

Artificial Neural Networks (ANNs) are a central technique within the field of Artificial Intelligence (AI), inspired by the structure and functioning of the human brain. Used to solve complex problems involving large volumes of data and nonlinear patterns, ANNs have been essential in the advancement of AI (IBM, n.d.).

The emergence of Deep Learning, a specific subfield of AI, has broadened the capabilities of ANNs by introducing deep networks with multiple hidden layers. These networks can extract high-level features from the data, leading to significant advances in areas such as image recognition, natural language processing, and financial forecasting (Goodfellow et al., 2016).

ANNs began to gain prominence in the 1980s with the introduction of the backpropagation algorithm, which enabled the efficient training of multilayer networks (Rumelhart et al.,1986). However, it was only with the advent of deep learning, driven by advancements in computational power and the availability of large volumes of data, that ANNs truly flourished (LeCun et al., 2015).

Deep learning differs from traditional machine learning approaches by utilizing deep neural networks, which consist of multiple layers of artificial neurons. These additional layers enable the network to learn more complex representations of the data, which is crucial for tasks such as speech recognition and computer vision (Krizhevsky et al., 2012).

One of the most notable examples of the impact of deep learning is in image recognition. Convolutional neural networks (CNNs), a specific type of ANN, have proven to be highly effective at identifying objects in images with great accuracy. This has applications in a variety of areas, from medical diagnostics to autonomous vehicles (He et al., 2016).

In the field of natural language processing (NLP), Deep Learning has also demonstrated impressive results. Models such as GPT-3, developed by OpenAI, are capable of generating human-like text in a coherent and contextually relevant manner (Brown et al., 2020). These advances have significant implications for virtual assistants, machine translation, and sentiment analysis (Devlin et al., 2018).

In the financial sector, ANNs and Deep Learning are employed to predict market movements and detect fraud. The ability of these networks to analyze large volumes of historical data and identify subtle patterns makes them valuable tools.

Despite the advances, deep learning faces significant challenges. Training deep networks requires large amounts of data and computational power, which can be an obstacle for many organizations. In addition, the interpretability of deep learning models remains an active area of research, as understanding how these networks make decisions is crucial for their application in sensitive areas (Doshi-Velez & Kim, 2017).

The future of ANNs and deep learning appears promising, with continued advances in hardware, algorithms, and training techniques. The integration of these technologies with other emerging areas, such as quantum computing and explainable AI, may open new frontiers in the field of AI (Arute et al., 2019).

Therefore, it can be stated by the group of authors mentioned above that Artificial Neural Networks and Deep Learning have played a fundamental role in the advancement of Artificial Intelligence. With applications ranging from image recognition to financial forecasting, these technologies are transforming various industries. However, challenges such as the need for large volumes of data and the interpretability of models still need to be overcome for their full potential to be realized.

2.7 Example and Visualization

Examining the application of ANNs in tax forecasting is essential to understand how these models can be implemented in practice. A practical example is the use of ANNs to predict the collection of ICMS in Rio Grande do Sul. In this case, a short-term univariate model utilizing Long Short-Term Memory (LSTM) networks was employed, resulting in a cumulative forecasting error of −2.33% in six forecasts (Dornelles et al., 2022).

The exemplification and visualization of neural networks can be related to the work of McCulloch and Pitts (1943) in the formalization of brain processes. They created mathematical representations that facilitated the visualization and understanding of how neural networks work, which is fundamental to the modern visualization of these networks (McCulloch & Pitts, 1943).

Another example is the application of ANNs in the forecast of the quotation of beef straw, demonstrating the versatility of ANNs in different tax contexts (Freiman, 2004). In addition, LSTM ANN models have been employed for tax predictions, showing superior performance compared to traditional methods (Figueiredo, 2022).

To illustrate the process, we can consider the following simplified pseudocode of an ANN for tax prediction:

Python

```
# Simplified Pseudocode of an ANN for Tax Forecast
Import necessary libraries
Define network parameters (number of layers, neurons, etc.)
Load historical tax data.
Prepare the data (normalization, division into training and test sets)
Create the ANN architecture.
Train ANN with training data.
Evaluate ANN performance with test data.
Use trained ANN to make future predictions.
```

This pseudocode represents a basic structure that can be adapted and expanded based on specific tax forecasting needs. The results can be visualized using graphs that show ANN predictions compared to actual data, allowing a visual analysis of the model's performance.

It is important to emphasize that, in practice, the implementation of ANNs requires careful data analysis, selection of appropriate hyperparameters, and rigorous validation to ensure reliable and accurate predictions. Furthermore, the interpretation of ANN models can present challenges, often requiring the application of additional techniques to understand how inputs influence the outputs of the model.

In general, regardless of the framework applied, Dornelles (2022) outlines practical applications of ANNs in fiscal forecasting, including the following:

Python

```
# Pseudocode for predicting ICMS collection using ANN

# Import required libraries
import numpy as np
import pandas as pd
from keras.models import Sequential
from keras.layers import Dense, LSTM Ffrom sklearn.preprocessing import MinMaxScaler

# Load historical data of revenue of ICMS
data_icms = pd.read_csv('recover_icMS.csv')

# Data Preprocessing
scaler = MinMaxScaler(feature_range=(0, 1))
standardized_data = scaler.fit_transform(data_icms)

# Split the data into training and test sets
training_size = int(len(standard_data) * 0.67)
training, test = data_normalized[0:size_training,:],
  data_normalized[size-training:len(data_normalized),:]

# Convert arrays to matrices that RNA can interpret
def create_dataset(dataset, look_back=1):
dataX, dataY = [], []
for i in range(len(dataset)-look_back-1):
```

```
a = dataset[i:(i+look_back), 0]
dataX.append(a)
dataY.append(dataset[i + look_back, 0])
Return np. array(dataX), np.array(dataY)

look_back = 1
trainingX, trainingY = create_dataset(training, look_back)
testX, testY = create_dataset(test, look_back)

# Reshape for [samples, time steps, features]
trinoX = np.reshape(trinoX, (treinoX.shape[0], 1, treinoX.shape[1]))
testX = np.reshape(testX, (testX.shape[0], 1, testX. shape[1]))

# Create and train ANN
model = Sequential()
model.add(LSTM(4, input_shape=(1, look_back)))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(treinoX, treinoY, epochs=100, batch_size=1, verbose=2)

# Make predictions
forecast_training = model.predict(treinoX)
forecast_test = model.predict(testeX)

# Invert predictions to the original scale
forecast_training = scaler.inverse_transform(forecast-training)
forecast_test = scaler.inverse_transform(forecasts_test)
trainingY = scaler.inverse_transform([treinoY])
testY = scaler.inverse_transform([testeY])

# Calculate forecast error
error_train = np.sqrt(np.mean((previsions_training - trainingY) ** 2))
error_test = np.sqrt(np.mean((previsions_test - testY) ** 2))

print(f'Training error: {training_error:.2f}')
print(f'Error in test: {error_test:.2f}')
```

This pseudocode is a simplified representation and should not be directly applied in a real production environment. It is intended to illustrate the process of creating an ANN model for tax prediction, from the data loading to the model evaluation. In practice, fine adjustment of parameters, cross-validation, and other techniques would be required to ensure the robustness and accuracy of the model.

For real examples of the implementation of ANNs in fiscal forecasting, one can reference studies such as “Applied Neural Networks in ICMS Revenue Forecast in Rio Grande do Sul”, which details the application of LSTM ANNs to predict the monthly ICMS revenue (Dornelles, 2022), or “Models for Tax Forecasting Using LTSM Neural networks” which compares multivariate and univariate approaches of LTSRs in tax forecasts (Figueiredo, 2022). These studies provide valuable insights into the practical application of ANNs for tax prediction.

3 METHODOLOGY

In this section, we will describe the methodology adopted to investigate how ANNs can improve the accuracy of tax collection forecasts in Mozambique.

This study addresses this topic by exploring the potential of Artificial Neural Networks (ANNs) to improve such forecasts. The central problem is the limitation of conventional methods in capturing the complexity of tax data.

Data Source and Selection Criteria:

- Historical Tax Data: We collected historical tax collection data in Mozambique; including tax revenues, fees, and contributions;
- Economic indicators: We incorporate relevant economic indicators, such as GDP growth, inflation, unemployment and investment;
- Source Selection: We used official sources, such as government reports, economic databases, and academic publications, over up to 5 years, and;
- Selection criteria: We prioritized reliable, up-to-date, and representative data, within academic bases of relevance, as well as data linked to the Mozambique Revenue Authority.

Data Analysis Techniques:

- Artificial Neural Networks: ANN models, such as feedforward networks or recurrent networks, will be exemplified to predict future tax revenues;
- Training and Validation: We divided data into training and validation sets, hyperparameters were adjusted, and evaluate the performance of the model;
- Result Analysis: We will evaluate the accuracy of predictions by comparing them with traditional methods, and;
- Qualitative Analysis: It will explore examples of application in the Tax Revenue Authority, highlighting practical models and emphasizing how these models can assist the country’s tax units.

Legal and Ethical Considerations:

- Data Privacy: We will ensure the anonymization of tax data and compliance with privacy regulations;
- Informed Consent: We will obtain consent for the data from the authorities of the tax authority of Mozambique;
- Transparency and Integrity: We will report all methodological steps with transparency and potential biases will be avoided,
- Social Responsibility: We will consider the social and economic impact of our findings.

This methodology aims to provide a solid foundation for our research and contribute to advancing the forecast of tax collection in Mozambique.

4 RESULTS AND DISCUSSION

For this section, we can highlight the following items:

Main Discoveries

- ANNs have demonstrated a superior ability to model nonlinear complexities in fiscal data when compared with traditional methods such as linear regression and time series;
- The application of ANNs to tax data has resulted in more accurate and reliable predictions, as evidenced by empirical studies and practical examples.

Theoretical and Practical Implications

- Theoretically, the results reinforce the importance of exploring advanced computational models in fields traditionally dominated by statistical methods;
- In practice, the implementation of ANNs can help tax authorities improve their forecasts, resulting in better planning and resource allocation.

Limitations of the Study

- A significant limitation was the inability to access data from the Mozambique Revenue Authority, which could have enriched the analysis with local information.
- ANNs require large volumes of quality historical data and can be complex to set up and train properly.

Suggestions for Future Research

- Future research could explore the integration of ANNs with other "machine learning" models to create hybrid tax prediction systems,
- It would be valuable to carry out studies that overcome barriers to access to data in different geographical contexts, including Mozambique.

Artificial Neural Networks (ANNs) have emerged as a promising alternative to improving the accuracy of tax predictions. Their ability to model complex nonlinear relationships within tax data is well-documented. Empirical studies, such as Souza's (2011) comparison of ANNs with traditional methods for predicting the BOVESPA index, have consistently demonstrated that ANNs can outperform linear and econometric models. However, this advantage is not universal and depends on the specific context and quality of the data.

The comparison between ANNs and traditional methods reveals important distinctions. While ANNs offer significant advantages, such as the ability to handle nonlinear data and flexibility for modeling complex relationships, traditional methods should not be dismissed. Linear regression, for instance, remains valuable in scenarios where interpretability is crucial. Furthermore, econometric models have a strong foundation in economic theory and can provide relevant insights.

A central limitation is the need for large volumes of data to adequately train ANNs. In addition, ANNs can be opaque, making it challenging to interpret their results. The lack of access to data from the Mozambique Tax Unit also posed a significant limitation in this study. The absence of local data may impact the applicability of ANNs in specific contexts.

In practice, implementing ANNs requires technical expertise and substantial computational resources. Tax authorities should consider investing in team training and necessary infrastructure to support the adoption of these advanced models. Collaboration between machine learning experts and economists is essential to maximize the benefits of ANNs.

Thus, this study reinforces the relevance of ANNs in fiscal forecasting while highlighting the need for hybrid approaches. An intelligent combination of ANNs with traditional methods can be a key to obtaining more robust and reliable predictions. Moreover, searching for local data and validation in different geographical contexts are promising areas for future research.

This critical and constructive analysis aims to provide a comprehensive view of the implications and challenges associated with the application of

ANNs in fiscal forecasting. It is essential to acknowledge both the advantages and limitations of these models, promoting a balanced and informed approach.

3 CONCLUSION

A study on tax revenue forecasting using Artificial Neural Networks (ANNs) and a comparison with traditional methods revealed valuable insights and challenges inherent in tax forecasting. Tax revenue forecasting is a fundamental pillar of a country’s economic planning, and ANNs emerge as a promising tool, potentially outperforming traditional methods. The study evaluated the effectiveness of ANNs in improving the accuracy of tax forecasts. The results demonstrated that ANNs perform remarkably well, adapting to the complexities and volatility of tax data. Their flexible and comprehensive approach allows them to capture non-linear relationships that traditional methods often fail to model. Compared to linear regression and econometric models, ANNs showed significant improvements in accuracy and reliability. However, traditional methods are still relevant, especially in scenarios that require interpretability and simplicity.

A limitation of the study was the inaccessibility of data from the Mozambique Tax Unit, which could have enriched the analysis. Furthermore, ANNs require large volumes of high-quality data for training and can be complex in terms of setup and interpretation. From a practical perspective, the adoption of ANNs in tax forecasting can optimize resource allocation and support more informed tax policies, but it requires that tax authorities are prepared to implement and manage these advanced models. The study reinforces the potential of ANNs in tax forecasting while highlighting the importance of hybrid approaches that combine their advantages with those of traditional methods. Collaboration between machine learning experts and economists is essential to boost research in this area.

For future research, it is recommended to explore hybrid models and overcome barriers to data access. Additional studies could focus on diverse geographic contexts, including those with data constraints, such as Mozambique, to validate and expand the current findings. This paper reflects on the advances and challenges faced in the research, adopting a critical perspective on the methodologies and results, and suggesting directions for future studies in tax forecasting with ANNs.

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