Chapter 5
Enhancing Portfolio Optimization With Deep Learning:
Evidence From African Stock Markets

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ABSTRACT

Emerging markets, particularly in Africa, present unique challenges for portfolio optimization due to increased volatility and limited historical data. This study explores the potential of deep learning models, specifically Long Short-Term Memory (LSTM), Deep Multilayer Perceptron (DMLP), and Convolutional Neural Networks (CNN), to predict the movements of three key African stock indices: MASI (Morocco), BRVM Composite (West Africa) and TUNINDEX (Tunisia). By comparing the performance of these architectures, this research aims to identify the models most suitable for prediction in a the context of limited data and high volatility. The results of this study will provide crucial insights for investors, portfolio managers, and researchers, thereby contributing to the development of more robust and effective portfolio optimization strategies for African markets, often overlooked by traditional methods.

1. INTRODUCTION

The field of portfolio optimization has long been a crucial aspect of financial management, as investors and financial professionals strive to construct portfolios that maximize returns while minimizing risks. Traditional approaches, such as the mean-variance optimization model developed by Harry Markowitz (1952), have provided valuable insights and tools for portfolio selection. However, the mean-variance (MV) model, while foundational in portfolio optimization, rests on several restrictive assumptions. One key assumption is the normal distribution of stock returns, which rarely holds true in real-world financial

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markets. Recognizing this limitation, researchers have explored alternative approaches to improve model accuracy. The Mean Absolute Deviation model, (Konno, H., & Yamazaki, H.1991) aims to replace the MV model. This model utilizes absolute deviation as a risk measure, thus providing ease of calculation for large-scale portfolio optimization problems. Furthermore, they demonstrate that this absolute deviation measure is equivalent to the variance measure when stock returns follow a normal distribution. The ARIMA (Autoregressive Integrated Moving Average) model (Saboia, 1977; Tsay, 2000), is another traditional statistical method used in portfolio optimization, it allows to predict time series based on linear relationships between past and present values. It is effective for stationary time series and has the advantage of being interpretable, allowing to understand the components of the series (trend, seasonality, etc.). On the other hand, ARIMA has its limitations, its primary weakness lies in its assumption of linearity, unable to capture complex and non-linear relationships present in many real data, which can lead to inaccurate forecasts. In addition, the ARIMA model primarily focuses on short-term temporal dependence, neglecting longer-term trends and structural changes in volatility, its sensitivity to outliers and the need for a precise model specification add additional complexity, increasing the risk of biased estimates and erroneous results. Although more sophisticated approaches such as the bilinear model (Poskitt & Tremayne, 1986), the threshold autoregressive model (Stark, 1992), and the autoregressive conditional heteroskedasticity (ARCH) model (Engle, 1982), are capable of extracting nonlinear signals in time series, they still require the series to be stationary. Proposed by Tim Bollerslev (1986), GARCH generalizes the ARCH model by including terms related to the past conditional variance. The GARCH model makes it possible to capture the effects of persistent volatility more efficiently with fewer parameters, which simplifies the estimation, as well as thanks to its components q (past variance) and p (past residuals), it captures long-term dynamics better.

The GARCH model offers a major advance to analyze time series with volatility fluctuations, an area where ARIMA and ARCH show their limits. Its effectiveness in financial data has made it an essential tool for researchers such as Engle and Bollerslev, who have revolutionized the modeling of conditional volatility.

Faced with the increased instability of financial markets, traditional portfolio optimization models struggle to effectively manage risks and maximize returns. The rise in volatility questions the validity of the linearity and stability assumptions on which this models are based. The emergence of deep learning, a branch of machine learning, offers new perspectives to improve financial forecasting and portfolio optimization (Heaton et al., 2017). Many studies have demonstrated the benefits of deep learning in portfolio optimization. For example, Gu, Kelly, and Xiu (2020) demonstrated that deep learning models can outperform traditional statistical models in terms of risk-adjusted performance. Similarly, the study of Jiang, Xu, Liang, (2017), indicate that deep learning can help better capture non-linear relationships and interactions between assets, leading to more efficient portfolios.

Recently, the use of various types of machine learning (ML) models deep neural networks especially, has become widespread for predicting financial markets, thereby contributing to improving portfolio optimization. Deep neural networks (DNNs) have shown better performance in predicting the financial market, so it is of great worth to explore the application of DNNs in formulating portfolio optimization models based on prediction.

This study explores the use of deep neural networks (DNN) to improve stock return predictions and optimize portfolio construction on three African stock markets: the MASI in Morocco, the BVRM in West Africa, and the TUNINDEX in Tunisia. The main objective is to evaluate and compare out-of-sample three types of DNN - the deep multilayer perceptron (DMLP), the long short-term memory neural