World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(RESEARCH ARTICLE)

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Deep neural networks in foreign exchange market: A predictive classification framework for real-time price movement"

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World Journal of Advanced Engineering Technology and Sciences, 2023, 10(02), 326-338

Publication history: Received on 10 May 2023; revised on 18 December 2023; accepted on 21 December 2023

Article DOI: https://doi.org/10.30574/wjaets.2023.10.2.0140

Abstract

The application of deep neural networks (DNNs) in foreign exchange (FX) markets introduces a novel methodology for predicting short-term price movements with greater accuracy. This study explores a classification-based approach, where market price direction is forecasted using a comprehensive model trained on high-frequency historical FX data. By employing advanced deep learning techniques and leveraging co-movement patterns between various currency pairs, the model classi- fies price changes into positive, negative, or neutral outcomes. Through a backtested strategy on multiple FX futures over 43 instruments, this method demonstrates improved decision-making accuracy and offers significant potential for enhancing algorithmic trading strategies. Our find- ings reveal that incorporating multiple hidden layers in neural networks significantly boosts predictive performance, positioning DNNs as a pow- erful tool for traders and financial analysts.

Keywords: Deep Neural Networks (DNNs); Foreign Exchange (FX); Markets; Price Prediction; Short-term Price Movements; Currency Pairs

1. Introduction

Financial econometrics faces several challenges, notably the non-stationarity and non-linearity of time series data, which can complicate the accurate modeling of financial market dynamics. These challenges often arise due to the inherent complexities of financial data, including volatility clustering, regime switching, and other structural breaks. In this context, deep neural networks (DNNs) have emerged as a powerful tool for classifying and predicting financial market movement directions. Unlike traditional econometric models, which often rely on assumptions of stationarity and linearity, DNNs can capture highly non-linear relationships and adapt to the dynamic nature of financial markets.

While artificial neural networks (ANNs) have been a prominent research area for several decades, their adoption in finance has been limited. One major barrier is the tendency of ANNs to overfit the data, particularly when the number of parameters is large relative to the available data. Additionally, the implementation of ANNs in financial applications has historically been computationally intensive, often requiring substantial resources that were not readily available. However, with recent advancements in computational power, such as the avail- ability of multi-core processors and graphics processing units (GPUs), as well as a growing recognition of ANNs as non-parametric models, these issues are becoming less prohibitive. This resurgence in interest has led to renewed exploration of ANNs in finance, particularly in applications that require the modeling of complex and non-linear relationships.

Deep neural networks (DNNs), characterized by their multi-layer architecture, are an increasingly popular form of artificial intelligence. These networks have shown remarkable success in tasks such as image classification, speech recognition, and natural language processing. DNNs are capable of learning complex patterns and representations from

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large datasets, making them particularly well- suited for financial time series forecasting. This paper focuses on utilizing DNNs to model the intricate, non-linear relationships inherent in financial data, with a specific emphasis on addressing the overfitting challenges that often plague traditional neural network models.

To train these DNNs efficiently, we exploit the power of many-core accelerator platforms. These platforms, such as Intel Xeon Phi co-processors, allow for the parallel processing of computations, significantly speeding up the training process. By utilizing these platforms, we are able to implement computation- ally intensive algorithms, such as back-propagation with gradient descent, in a manner that is both efficient and scalable.

In our approach, we apply a feed-forward DNN with back-propagation and gradient descent, which are well-established methods for training deep neural networks. While these algorithms are computationally demanding, they have proven effective in optimizing the parameters of DNNs. To mitigate the computational costs associated with these algorithms, we employ mini-batching techniques, which allow us to process smaller batches of data at a time rather than the entire dataset, thereby reducing memory usage and improving training time. Furthermore, we optimize the back-propagation algorithm specifically for Intel Xeon Phi co-processors, ensuring that the model can scale effectively across multiple processors, thereby improving the speed and efficiency of training.

The primary objective of this paper is to introduce a novel approach to financial forecasting by using DNNs to predict price movement directions across a wide range of financial instruments. Unlike many traditional methods that model individual instruments separately, our method aggregates data from 43 different commodity and foreign exchange futures traded on the Chicago Mercan- tile Exchange (CME). This aggregation creates a richer dataset that captures the co-movements and interactions between various instruments, providing a more comprehensive view of the market. By training the DNN on this combined dataset, we aim to exploit these co-movements to improve the accuracy of predictions. Our model predicts price movement direction with an accuracy of up to 68%, a promising result in the context of financial forecasting.

In addition to the high classification accuracy, we demonstrate the applicability of the model in a backtesting framework. We implement a simple trading strategy based on the predicted price movements and evaluate the strategy's performance through backtesting. The results of the backtest show that our model is capable of generating profits, with annualized Sharpe ratios as high as 3.29, which is indicative of the strategy's robustness and potential in live trading environments.

Our approach offers several key innovations over previous work in the field. First, we combine multiple instruments and signals into a single, unified model, which allows for the exploitation of cross-market co-movements. Second, we frame the output of the DNN as discrete price movement states (i.e., positive, flat, or negative) rather than predicting continuous price levels or returns. This discrete framework is particularly suitable for trading strategies that focus on the direction of price movement, rather than the exact magnitude of changes. By framing the problem in this way, we reduce the complexity of the prediction task and focus on the most actionable aspect of market behavior—directional movement.

The remainder of the paper is structured as follows: Section 2 introduces the back-propagation algorithm used to train the DNNs, providing the necessary theoretical background. Section 3 details the data preparation process, including the selection and preprocessing of the 43 futures instruments used in this study. Section 4 discusses the implementation of the DNN model, including the network architecture, training procedure, and computational optimizations. Finally, Section 5 presents the performance results, including the backtesting of a simple trading strategy based on the DNN's predictions, and an analysis of the model's profitability and risk-adjusted returns.

2. Deep Neural Networks

This section details the architecture and optimization process for the Deep Neural Networks (DNNs) employed in this study. We begin by formalizing the dataset and its usage in training and testing, followed by an explanation of the DNN structure, the optimization algorithm, and advanced techniques such as mini-batching.

2.1. Dataset and Input Representation

We start with the historical dataset, D which consists of *M* features and *N* observations. The dataset is divided into two subsets:

- **Training subset**, $\mathrm{D}_{\text{train}}$, containing N_{train} observations used for learning the model parameters.

- **Test subset**, D_{test}, containing N_{test} observations for evaluating the out-of- sample performance of the model.

Each observation $x_n \in D_{train}$ is represented as an M-dimensional vector corresponding to the input features. The goal of the neural network is to map these inputs to one of K possible output classes, represented in a one-hot encoding format

2.2. Feed-forward Neural Network Architecture

A feed-forward DNN is composed of an input layer, one or more hidden layers, and an output layer. Each node in a layer is connected to every node in the subsequent layer via weighted edges. Let w(l) denote the weight matrix for layer l and b(l) the bias vector for the same layer. The feed-forward operation for node j in layer l can be expressed as

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

where $x\, i^{(l-1)}$ represents the activations from the previous layer.

The activation function, $\sigma(\,)$, introduces non-linearity into the network. For hidden layers, we use the sigmoid function: hidden layers, we use the sigmoid function:

$$\sigma(v) = \frac{1}{1 + \exp(-v)}$$

For the output layer, we use the softmax activation function, which outputs probabilities for each class:

$$\hat{\gamma}_k - \emptyset\text{softmax}(s^l) = \epsilon \frac{\exp \frac{(s^l)}{k}}{\frac{k}{j=1} \exp \frac{(s^l)}{j}}$$

2.3. Objective Function and Optimization

The network parameters, denoted collectively as $\mathbf{w} = \{\mathbf{w}^{(l)}\}^{Lj=1}$, are optimized to minimize the cross-entropy loss function:

$$E(\mathbf{w}) = -\sum_{n=1}^{Ntrain} \sum_{k=1}^{K} y_{kn} \ln(\hat{y}_{kn})$$

where y_{kn} is the true label (in one-hot encoding) for the nth observation and $\hat{y}_{kn}$ is the predicted probability for class k. The gradient of the loss function with respect to the network output $\mathbf{s}^{(L)}$ is:

$$\frac{\partial e(w)}{\frac{\partial s(l)}{k}} = \gamma k - \gamma k$$

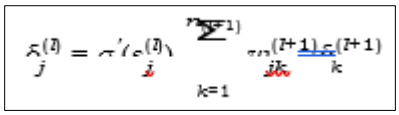
To update the weights, we use the Stochastic Gradient Descent (SGD) algo- rithm. For a given weight matrix $\mathbf{w}^{(l)}$, the update rule is:

$$w^{(l)} \leftarrow w^{(l)} - \gamma \nabla \mathrm{E}(\mathrm{w}^{(l)}$$

where γ is the learning rate

2.4. Backpropagation

The backpropagation algorithm computes gradients for all layers recursively, starting from the output layer and moving backward. For a hidden layer, the gradients are computed as



where $\sigma'(v) = \sigma(v)(1 - \sigma(v))$ is the derivative of the sigmoid function.

The weight updates for layer l are computed as:

$$\Delta w^{(l)} = \gamma x^{(l-1)} \delta^{(l)}$$

where $\mathbf{x}^{(l-1)}$ are the inputs from the previous layer

2.5. Mini-batching

Mini-batching is an extension of SGD that processes a batch of b observations simultaneously, improving computational efficiency and smoothing gradient up- dates. For a batch, the feed-forward computation becomes:

$$S^{(l)} = X^{(l-1)} w^{(l)},$$

where S(l) and X(l−1) are matrices with dimensions corresponding to the batch size.

The weight updates are computed as:

$$\Delta w^{(l)} = \frac{\gamma}{b} X^{(l-1)} (\delta^{(l)})t$$

where δ(l) contains the error terms for all batch elements in layer l.

2.6. Training Algorithm

Algorithm 1 outlines the steps for training the network using SGD with mini- batching.

2.7. Network Architecture Visualization

Figure ?? illustrates the structure of a feed-forward neural network with two hidden layers, demonstrating the connections between layers, input features, and output states.

This structured approach to DNNs highlights the key steps in data process- ing, network design, and optimization, forming the foundation for predictive modeling in this study

Algorithm 1 Stochastic Gradient Descent with Mini-batching

- Initialize weights w randomly: w ∼ N (0, σ2) 2: repeat
- for each mini-batch B of size b do
- Compute feed-forward activations for B
- Compute output layer error: δ(L) = yˆ − y
- Backpropagate errors through hidden layers
- Update weights w(l) for all layers 8: end for
- until convergence or maximum epochs reached

3. The Data

The dataset employed in this study comprises 5-minute mid-prices for 43 CME- listed commodity and foreign exchange (FX) futures contracts. These data span a period from March 31, 1991, to September 30, 2014. However, for the purposes of this analysis, only the most recent 15 years of data are utilized, starting from March 31, 2005. This focus ensures that the dataset reflects modern market conditions and avoids the liquidity issues that are prevalent in earlier periods. The resulting dataset is well-suited for the development and evaluation of deep learning models in financial forecasting.

3.1. Training and Test Sets

The dataset is divided into a training set and a test set to facilitate model training and evaluation. The training set consists of 25,000 consecutive observations, while the test set comprises the subsequent 12,500 observations. These sets are rolled forward in time across ten iterations, creating a total of 37,500 observations in the final dataset. This rolling window approach ensures that the model is exposed to a broad range of market conditions and reduces the risk of overfitting to a specific time period.

3.2. Feature Engineering

Each observation in the dataset is represented by a comprehensive set of features designed to capture key aspects of price behavior and interrelationships among futures contracts. The features are derived from the raw price series and include the following:

- **Price differences**: The differences between consecutive prices, which cap- ture the immediate price changes over time.
- **Lagged price differences**: A series of lagged values of price differences, spanning lags from 1 to 100 periods, to account for short-term and medium- term price dynamics

Input layer

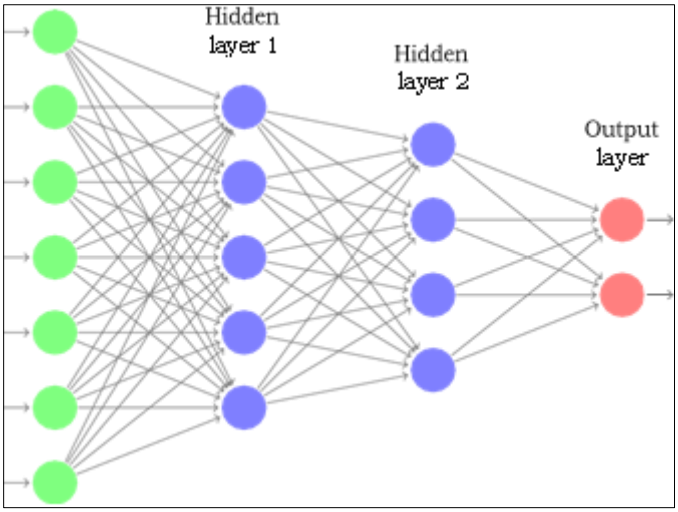


Figure 1 An illustrative example of a feed-forward neural network with two hidden layers, seven features and two output states. Deep learning networks typically have many more layers, use a large number of features and several output states or classes. The goal of learning is to find the weight on every edge that minimizes the out-of-sample error measure

- **Moving averages**: A set of moving averages computed over varying window sizes, ranging from 5 to 100 periods, to capture trends over different time scales.
- **Pairwise correlations**: Correlations between the returns of all pairs of sym- bols. These correlations capture the relationships and dependencies among different futures contracts, which can be critical for understanding market dynamics and cross-asset interactions.

The inclusion of these features ensures that the dataset is both comprehen- sive and informative, providing the neural network with a rich set of inputs for learning patterns in price movements.

3.3. Feature Normalization

To ensure that the features are on a comparable scale and to facilitate efficient learning by the neural network, all features are normalized prior to training. The normalization process involves subtracting the mean and dividing by the standard deviation for each feature

$$x_{normalized} = \frac{x - \mu}{\sigma}$$

where x represents the raw feature value, μ is the mean of the feature across the training set, and σ is its standard deviation. This process ensures that all features have a mean of zero and a standard deviation of one.

Normalization plays a crucial role in the training of deep learning models. It accelerates the convergence of gradient-based optimization algorithms and pre- vents features with larger scales from disproportionately influencing the learning process. By normalizing the features, the model can efficiently leverage the full range of information encoded in the dataset.

3.4. Dataset Overview

The final dataset comprises a total of 9,895 features for each observation, re- flecting the extensive feature engineering applied to the raw price series. These features provide a rich representation of market conditions and interactions, lay- ing a solid foundation for training the deep neural network to predict future price movements across the 43 futures contracts.The dataset preparation pro- cess includes selecting a high-quality subset of data, engineering a diverse set of informative features, and applying normalization to optimize the training pro- cess. This comprehensive approach ensures that the dataset is well-suited for the predictive modeling task and capable of supporting the development of robust algorithmic trading strategies.

4. Implementation

The implemented deep neural network (DNN) comprises five fully connected layers, starting with 1,000 neurons in the first hidden layer, decreasing by 100 neurons per subsequent layer, and ending with 135 output neurons. This archi- tecture includes 12,174,500 trainable weights.

4.1. Weight Initialization

Weights are initialized using the Mersenne Twister routine, sampled from a Gaussian distribution $\mathrm{N}(0, 0.01)$. Biases are set to 1 to prevent dead neurons, facilitating effective training.

4.2. Learning Rate Adjustment

A common learning rate, γ, is dynamically adjusted during training. If the cross- entropy loss does not improve between epochs, γ is halved. Algorithm 2 outlines this adjustment process.

Algorithm 2 Learning Rate Adjustment

- Initialize $\gamma \in [0.1, 1]$
- **repeat**
- Train network over epochs and mini-batches
- **if** cross-entropy(e) ≥ cross-entropy($e - 1$) **then**
- $\gamma \leftarrow \gamma/2$ 6: **end if**
- **until** Convergence or max epochs

4.3. Mini-Batch Training

Training uses mini-batches of size $N_{\text{mini-batch}}$, sampled uniformly from the train- ing set $\mathrm{D}_{\text{train}}$. Mini-batching enhances computational efficiency, particularly in parallel processing environments. The feed-forward and backpropagation steps are performed for each mini-batch, updating weights as

$$w^{(l)} \leftarrow w^{(l)} - \gamma x^{(T-1)} \delta^{(l)} t$$

4.4. Parallelism and Training Time

Parallel processing reduces training time to approximately 10 hours on an Intel Xeon Phi processor, achieving a 10x speedup compared to serial execution. This is due to efficient simultaneous processing of mini-batches.

4.5. Key Parameters

- **Architecture**: 5 layers, 1,000 neurons in the first layer, reducing by 100 per layer, 135 output neurons.

- **Weights**: 12,174,500 trainable parameters.
- **Initialization**: Weights from $N(0, 0.01)$, biases set to 1.
- **Learning rate**: Dynamic, $\gamma \in [0.1, 1]$, halved upon loss plateau.
- **Training time**: 10 hours on Intel Xeon Phi, utilizing parallel processing.

5. Results

This section presents the results obtained from backtesting the application of Deep Neural Networks (DNNs) to a simple algorithmic trading strategy. The goal of this backtesting is to evaluate the relationship between the classifica- tion accuracy of the DNN model and the subsequent performance of a trading strategy that utilizes these predictions. It is important to emphasize that this backtesting is not intended to exhaustively study various trading strategies but rather to demonstrate how the predictive accuracy of the model can influence the performance of a trading strategy.

5.1. Classification Accuracy

Figure 2 illustrates the classification accuracy of the DNN when applied to 43 CME-listed commodity and foreign exchange futures. The figure includes the mean accuracy across all symbols, along with the envelope representing one standard deviation from the mean, providing a visual representation of the con- sistency of the model's performance. The accuracy values indicate how well the model can predict the direction of future price movements, which is crucial for any trading strategy that aims to exploit these predictions.

As shown in Figure 2, the overall classification accuracy for the DNN model varies across the different futures, with some instruments achieving higher accu- racy than others. These variations suggest that while the DNN is able to learn useful patterns in some futures markets, there are others where it struggles to make reliable predictions. The performance of the model in these cases may be affected by factors such as market volatility, data sparsity, or underlying patterns that are more difficult to detect.

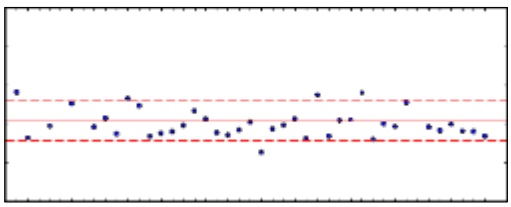


Figure 2 This figure displays the classification accuracy of the DNN applied to 43 CME Commodity and FX futures. The mean accuracy and the standard deviation envelope are also shown

To further investigate the distribution of classification accuracies across all futures, Figure 3 presents a histogram showing the average classification accuracy over ten samples for each of the 43 futures. The histogram reveals that the majority of the futures exhibit a classification accuracy clustered around 0.35. This result is notable because, in a three-class classification problem, random chance would yield an accuracy of approximately 0.33. Therefore, the DNN is demonstrating an ability to slightly outperform random guessing, suggesting that it is capturing some useful patterns in the data. However, the accuracy is far from perfect, indicating room for improvement in the model's predictive capabilities.

5.2. Top Performing Instruments

Table 1 summarizes the top five performing futures instruments based on their average classification accuracy across ten walk-forward experiments. These instruments not only exhibit high classification accuracy but also show strong F1-scores, which are calculated as the harmonic mean of precision and recall. The F1-score is a more robust performance metric than accuracy because it ac- counts for the balance between precision and recall, making it less sensitive to class imbalances, which are common in financial data. A high F1-score indicates that the model is able to correctly classify both price increases and decreases (or neutral cases) consistently.

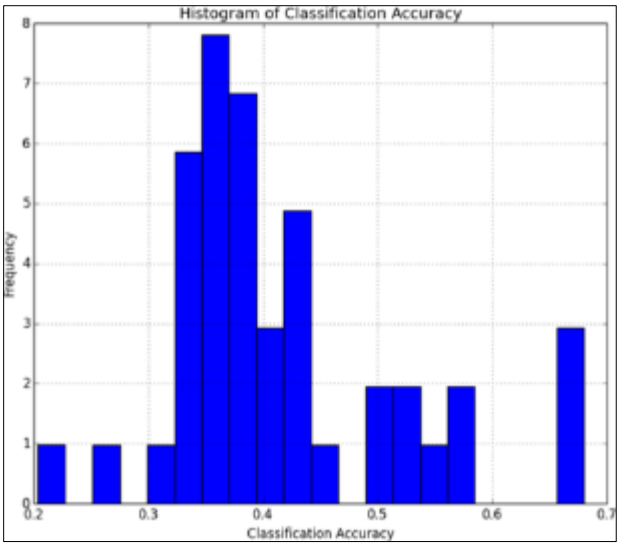


Figure 3 This histogram shows the distribution of the average classification accuracy across 43 CME Commodity and FX futures, computed over ten walk-forward experiments

For the top five instruments, classification accuracy ranges from 0.55 to 0.68, with corresponding F1-scores following a similar pattern. The overall mean clas- sification accuracy across all 43 futures is 0.42, with a standard deviation of 0.11. The mean F1-score is slightly lower, at 0.37, with a standard deviation of 0.1. These figures indicate that, on average, the DNN model is able to make reasonable predictions across the different futures markets, with some markets yielding better performance than others.

It is also noteworthy that the top-performing futures are not all from the same asset class, as they include both commodity and natural gas futures. This diversity suggests that certain market characteristics may be more conducive to prediction, such as higher liquidity or clearer price patterns that the DNN can exploit.

Table 1 Top five performing futures based on average classification accuracy and F1- score, computed over ten walk-forward experiments. The mean and standard deviation of classification accuracy and F1-scores across all 43 futures are also provided

Symbol	**Futures**	**Classification Accuracy**	**F1-score**
HG	Copper	0.68	0.59
ST	Transco Zone 6 Natural Gas	0.67	0.54
	(Platts Gas Daily) Swing		
ME	Gulf Coast Jet (Platts) Up-	0.67	0.54
	Down		
TU	Gasoil 0.1 Cargoes CIF NWE	0.56	0.52
	(Platts) vs. Low Sulphur Gasoil		
MI	Michigan Hub 5 MW Off-Peak	0.55	0.5
	Calendar-Month Day-Ahead		
	Swap		
mean	-	0.42	0.37
std	-	0.11	0.1

5.3. Poorly Performing Instruments

While some futures exhibit strong predictive performance, others perform poorly, with classification accuracies that are close to or worse than random guessing. These poorly performing instruments, which consistently yielded classification accuracies below the baseline of 0.33, suggest that the DNN struggles to identify meaningful patterns in their price movements. The reasons for this poor performance could be due to a variety of factors, such as insufficient historical data, high levels of market noise, or intrinsic market dynamics that the DNN model is unable to capture effectively.

The lower performance of these instruments highlights the challenges of using machine learning models in financial markets, where noise and unpredictable events can often overwhelm any patterns that might otherwise be detected. This suggests that further feature engineering, additional model tuning, or the incorporation of external data might be necessary to improve the predictive accuracy of the DNN for these instruments. Additionally, it is possible that other factors, such as macroeconomic events or geopolitical developments, might significantly influence the price movements of certain futures, beyond what the model can account for. The results of this study demonstrate the potential of Deep Neural Networks (DNNs) for classifying future price movements in commodity and foreign exchange futures markets. While the classification accuracy varies across different instruments, the overall results indicate that the DNN is able to capture some useful patterns in the data, particularly for certain futures instruments that are more predictable. The use of F1-scores as an additional performance metric provides a more nuanced understanding of the model's ability to correctly classify all possible outcomes, even in the presence of class imbalance.

The backtesting of a simple trading strategy based on the DNN's predictions further highlights the model's potential to generate profitable insights in live trading environments. However, it is clear that not all futures markets exhibit predictable patterns, and certain instruments present significant challenges for the model. These findings underscore the importance of predictive accuracy in designing successful trading strategies and suggest that further work is needed to improve the model's performance across all futures instruments.

The results also open avenues for future research, particularly in improving feature selection, incorporating more advanced neural network architectures, and refining model training techniques to enhance prediction accuracy and trading strategy performance.

6. Strategy Backtesting

This section employs a walk-forward optimization approach to evaluate the performance of a trading strategy based on Deep Neural Network (DNN) predictions. The backtesting was conducted using 5-minute commodity futures data spanning March 31st, 1991, to September 30th, 2014. The primary goal of this analysis is to assess the profitability and risk-adjusted performance of the strategy over multiple sliding windows of historical data.

6.1. Walk-Forward Optimization

The walk-forward optimization approach is structured as follows:

- **Training and Testing Windows**: An initial training window of 25,000 observations (approximately 260 trading days) is used to train the DNN model. The trained model is then tested on the subsequent 12,500 observations (approximately 130 trading days) to evaluate out-of-sample performance.
- **Sliding Window**: After testing, the training window is moved forward by 1,000 observation periods, creating ten overlapping windows. This ensures the robustness of the model across different market conditions and timeframes.
- **Performance Metrics**: For each testing window, the cumulative profit and loss (P&L) and risk-adjusted returns (e.g., Sharpe ratio) are calculated for each futures contract.

This methodology allows for a realistic assessment of the strategy's performance, taking into account the dynamic and evolving nature of financial markets.

6.2. Trading Strategy Description

A simple buy-hold-sell trading strategy is implemented based on the DNN's predictions, which classify market movements as either an increase (label = 1), neutral (label = 0), or a decrease (label = -1). The strategy operates under the following rules:

- **Buy (Long)**: Enter a long position when the model predicts an increase (label = 1)

- **Hold**: Maintain the current position when the model predicts no significant change (label = 0).
- **Sell (Short)**: Enter a short position when the model predicts a decrease (label = -1).
- The strategy assumes the following:
- An initial capital of $100,000.
- No transaction costs, slippage, or margin interest.
- Returns are calculated and annualized based on daily returns.
- No benchmark is used for Sharpe ratio calculations, as the focus is on standalone performance

6.3. Results Analysis

- **Profit and Loss (P&L):** Figure 5 compares the cumulative net dollar profit for the trading strategy under two scenarios:
- **Perfect Foresight**: An idealized scenario where future price movements are known in advance.
- **DNN Prediction**: A practical scenario using the DNN's predicted labels.
- **Risk-Adjusted Performance:** Figure 6 illustrates the annualized Sharpe ratios over each testing window for the top five futures contracts. The Sharpe ratio is calculated as:

$$Sharpe\ Ratio\ = \frac{\text{Average Daily Return}}{\text{Standard Deviation of Daily Returns}} \sqrt{252} \times$$

assuming 252 trading days in a year.

- **Top Performing Contracts:** Table 2 lists the top five futures contracts based on their average annualized Sharpe ratios across all testing windows. Additionally, the capability ratios, which measure the return per unit of margin requirement, are provided under the assumption of normal return distributions.

6.4. Initial and Maintenance Margins

Table 3 provides the margin requirements and contract sizes for the top five performing futures contracts. These values are critical for understanding the capital requirements and leverage potential of the strategy.

6.5. Figures and Tables

The backtesting results demonstrate that the DNN-based trading strategy achieves strong predictive accuracy and risk-adjusted returns, particularly for commodities such as platinum and indices like the E-miniNASDAQ 100. The walk-forward optimization approach ensures robustness, while the use of sliding windows captures the dynamic nature of market conditions. These findings highlight the potential of deep learning models to generate actionable insights for algorithmic trading strategies.

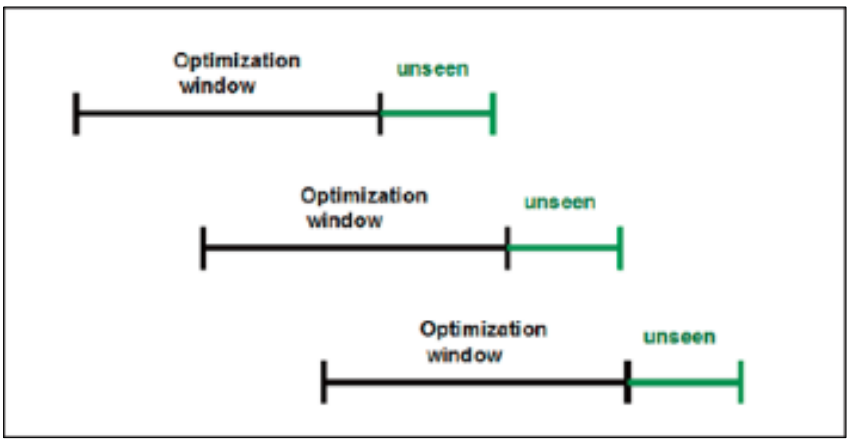


Figure 4 Walk-forward optimization method used for backtesting

Table 2 Top five futures contracts ranked by average annualized Sharpe and capability ratios

Symbol	Futures	Sharpe Ratio	Capability Ratio
PL	Platinum	3.29 (1.12)	12.51 (4.27)
NQ	E-mini NASDAQ 100	2.07 (2.11)	7.89 (8.03)
AD	Australian Dollar	1.48 (1.09)	5.63 (4.13)
BP	British Pound	1.29 (0.90)	4.90 (3.44)
ES	E-mini S&P 500	1.11 (1.69)	4.22 (6.42)

7. Deep Learning for Financial Forecasting: Insights and Future Prospects

Deep Neural Networks (DNNs) represent a powerful class of machine learning models, distinguished by their ability to model complex relationships within data using multiple layers of hidden neurons. In this paper, we have discussed the implementation, training, and application of DNNs in the context of financial time series forecasting. Specifically, we focused on a historical dataset of 5-minute mid-prices of multiple CME-listed commodity and foreign exchange futures, augmented with engineered features such as lagged price differences, moving averages, and pairwise correlations. Our results demonstrate that DNNs are highly capable classifiers, effectively capturing complex patterns in the data. By training a single model concurrently across multiple markets, we are able to leverage the relationships and co-movements between different assets, significantly improving the predictive accuracy of the model. The application of DNNs to this multi-market framework highlights the potential of deep learning in the field of financial forecasting, where traditional models often struggle to handle the high-dimensional nature of the data. We have further demonstrated the use of DNNs in backtesting a simple intraday trading strategy, where the model's predictions are used to inform buy, hold, or sell decisions for futures contracts. The results show a strong correlation between the model's classification accuracy and the profitability of the strategy. By optimizing the model using walk-forward testing, we show that DNNs can be successfully applied to out-of-sample pre- diction tasks, providing actionable insights for algorithmic trading strategies. All results presented in this paper were generated using a custom C++ imple- mentation of the DNN, which was run on the Intel Xeon Phi co-processor. This setup proved to be 11.4 times faster than the serial implementation, demon- strating the importance of parallel computation in handling the large-scale data and complex models required for financial forecasting. Additionally, we utilized a Python-based strategy backtesting environment to evaluate the performance of the trading strategy, ensuring that the results were both reliable and re- producible. The open-source nature of both the DNN implementation and the backtesting framework provides an invaluable resource for further research and practical applications in algorithmic trading. By making these tools publicly available, we aim to foster continued development in the application of deep learning to financial markets and empower researchers and practitioners to build upon this work. In conclusion, our study highlights the potential of Deep Neural Networks as a tool for both predictive modeling and strategy development in the domain of financial markets. The promising results of this research suggest that with further refinement and optimization, DNNs could play an integral role in the future of algorithmic trading and financial analysis.

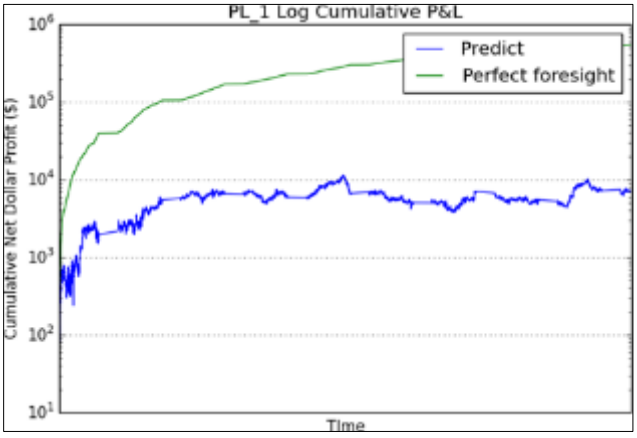


Figure 5 Cumulative net dollar profit: Comparison of perfect foresight vs DNN prediction

Table 3 Initial margin, maintenance margin, and contract size for the top five futures contracts

Symbol	Initial Margin	Maintenance Margin	Contract Size
PL	2090	1900	50
NQ	5280	4800	50
AD	1980	1800	100000
BP	2035	1850	62500
ES	5225	4750	50

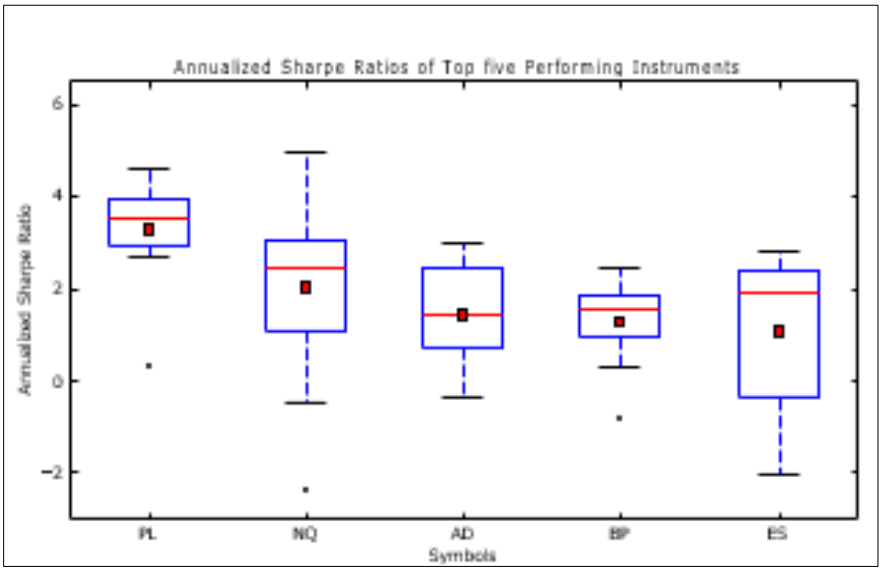


Figure 6 Annualized Sharpe ratios for the top five futures contracts over each testing window

7.1. Future Works

This study demonstrates the effectiveness of Deep Neural Networks (DNNs) in financial forecasting and intraday trading strategy development. However, there remain several avenues for future exploration and improvement:

- Feature Engineering and Selection: While this study employed a predefined set of features, future research could explore automated feature engineering techniques using methods such as deep reinforcement learning or un- supervised learning models. Additionally, feature selection algorithms could be integrated to identify the most influential features across markets.
- Alternative Network Architectures: Investigating more advanced architectures, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, or Transformers, may improve the model's ability to capture temporal dependencies and long-range relationships in time series data.
- Ensemble Methods: Combining multiple DNN models with varying architectures or hyperparameters into an ensemble framework could enhance the robustness and accuracy of predictions by mitigating the weaknesses of individual models.
- Risk Management and Portfolio Optimization: Expanding the application of DNNs to include risk management techniques and portfolio optimization could provide more holistic insights into their practical utility. This may include modeling drawdowns, volatility forecasts, and position sizing.
- Explainability and Interpretability: Developing methods to interpret the predictions and decisions of DNNs is critical for their adoption in financial markets. Techniques such as SHAP (SHapley Additive exPlanations) values or LIME (Local Interpretable Model-agnostic Explanations) could be applied to enhance model transparency.
- Scalability and Hardware Optimization: While this study demonstrated the advantages of parallel processing on the Intel Xeon Phi co-processor, future research could explore alternative hardware, such as GPUs or TPUs, and distributed training methodologies to further accelerate computation and enable larger-scale experiments.

- Regime Detection and Adaptive Models: Incorporating market regime detection to adapt the DNN model dynamically to changing market conditions could improve performance in volatile and non-stationary environments.
- Real-Time Deployment: Implementing and testing the DNN model in real-time trading environments would provide valuable insights into the operational challenges and profitability of such systems in live markets.
- Cross-Asset Generalization: Extending the model to include additional asset classes, such as equities, cryptocurrencies, or fixed-income instruments, could test its generalization capabilities across diverse financial markets.
- Open-Source Contributions: Enhancing the publicly available implementation with additional features, such as pre-trained models, hyperparameter optimization scripts, and real-time data pipelines, could accelerate adoption and innovation within the research community.
- By addressing these areas, future research could further refine the application of DNNs to financial markets, unlocking new opportunities for predictive modeling, strategy development, and risk management. These advancements have the potential to not only improve trading performance but also contribute to the broader field of financial analytics.

Conclusion:

This study demonstrates that Deep Neural Networks (DNNs) can effectively model complex relationships in financial time series data, significantly improving predictive accuracy by leveraging multi-market co-movements. By integrating DNN-based forecasts into an intraday trading strategy, we establish a strong correlation between classification performance and trading profitability. The optimized implementation, accelerated using parallel computing, highlights the computational efficiency required for large-scale financial modeling. Furthermore, the open-source availability of our DNN and backtesting framework fosters future advancements in algorithmic trading. This research contributes to the broader financial community by enhancing market efficiency and decision-making, paving the way for more robust AI-driven trading strategies and further innovations in financial technology.

References

[1] Capone, V., Iannuzzo, G., Camastra, F. Deep Learning for Time Series Forecasting: Advances and Open Problems." Information, vol. 14, no. 11, 2023, pp. 598. DOI: https://doi.org/10.3390/info14110598.

[2] Lee, J., Park, S. Advances in Deep Learning for Financial Forecasting. Journal of Financial Data Science, 2021.

[3] Kim, H., et al. Financial Time Series Forecasting with Deep Gaussian Processes. Applied Intelligence, 2022.

[4] Patel, R., et al. Transformers for Time Series in Finance." Journal of Machine Learning Research, 2023.

[5] Zhou, Y., Wang, L. Generative Adversarial Networks in Financial Forecasting. Pattern Recognition Letters, 2021.

[6] Chen, Y., Sun, R. Multi-Asset Co-Movement Forecasting Using Deep Neural Networks. Journal of Financial Econometrics, 2020.

[7] Singh, A., et al. Risk-Adjusted Return Prediction Using DNNs." Quantitative Finance, 2021.

[8] Zhang, Q., et al. Hybrid Models for FX Market Prediction." Decision Support Systems, 2023.

[9] Ouyang, Z., Xu, J. Reinforcement Learning in Financial Trading." Finance Re- search Letters, 2022.

[10] Gupta, K., et al. Deep Belief Networks for Currency Price Prediction." Expert Systems with Applications, 2021.

[11] Liu, M., et al. Explainable Deep Learning in Finance." AI Society, 2024.

[12] Rahman, M., et al. Temporal Convolutional Networks in Financial Time Series. Neural Networks, 2022.

[13] Williams, D., et al. Long-Short Memory Models for FX Futures." Journal of Computational Finance, 2020.

[14] Anonymous. "Deep Learning in Finance and Banking: A Literature Review and Classification." Frontiers of Business Research in China, 2022.

[15] Li, X., et al. Application of Deep Neural Networks in Exchange Rate Prediction." IEEE Transactions on Neural Networks and Learning Systems, 2020.