ANN model for Call Options Pricing using S&P 100 Market Data

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Abstract: - Stock options pricing is of key importance for markets and traders and is largely based on theoretical models like the Black-Scholes model. However, developments in machine learning open a novel, data-driven, perspective in contrast to the theoretical ones. This work explores the feasibility of artificial neural network model utilization for call option pricing, using the traditional Black-Scholes model as a benchmark. A multilayer perceptron model is trained to learn the Black-Scholes function and tested in real market call options data originating from thirty-five S&P 100 stocks. Findings demonstrate that artificial neural networks perform relatively well with market data and can be a valid data-driven approach for call option pricing, competitive to Black-Scholes. A unique contribution of this study is that testing data is not derived from the same distribution as training data, something common in existing works with similar models. Although further exploration and experimentation are required to reach the required robustness and become less ad hoc and data sensitive, data-driven pricing using artificial neural networks is a promising approach and can play a substantial role in option pricing.

Key-Words: - option pricing, artificial neural network, multilayer perceptron, call options, Black-Scholes model, machine learning, deep learning.

Received: March 8, 2023. Revised: November 4, 2023. Accepted: December 6, 2023. Published: January 25, 2024.

1 Introduction

Stock options comprise a dynamic domain in financial research and numerous models have been proposed during the past few decades for their efficient pricing. The older and more traditional models rely mainly on theory, while recent developments in pricing include models that rely on data. The major characteristic and benefit of the conventional models, like the seminal Black-Scholes model, is that they offer closed-form mathematical solutions, something that makes them very valuable approaches for pricing in market conditions. They are very popular due to their speed, flexibility, and accuracy, however, they are quite limited, as only some option types can be supported and only if specific assumptions and parameter values are met. On the other hand, alternative models exist, relying on numerical procedures, like Monte Carlo simulation and the Binomial model. These approaches follow theoretical constructs and simulate the behavior of underlying assets to estimate option prices. These models can support a wider set of option types compared to the limited Black-Scholes model, [1], [2], [3], [4]. The key limitation of conventional approaches is that they are theoretical abstractions and, as such, they are not able to capture the entire complexity and dynamics of the underlying process market mechanisms. So, they inevitably have limitations in assumptions, or their parameters and they do not perform accurately or promptly in every setting or option type.

Following the developments in machine learning and artificial neural networks, researchers in the domain proposed novel option pricing models that rely on data instead of theory. These models use either empirical or artificially generated data for training and testing and they do not require any theoretical construct beforehand. Artificial neural network approaches are the most representative approach from this group of methods, and they can be competitive with conventional models in many option types. Machine learning models, and especially artificial neural networks, can model any kind of nonlinear behavior and interaction, without the need of underlying theoretical abstraction. However, their approach makes it very hard to generate an explainable model, something that is an inherent feature of artificial neural networks. So, their black-box behavior, even if the model is successful in pricing, remains an issue for researchers. Also, machine learning models require large volumes of data to be trained accurately, which is not always feasible. Additionally, as they rely on the training approach and dataset, they tend to be domain and data-specific, rather than universal as compared to the traditional models. So, even if machine learning-based models are becoming a competitive alternative to traditional pricing methods, further research is necessary to offer more robust and widely used approaches, [5], [6], [7], [8], [9].

Following the above, this work explores the feasibility of using artificial neural networks in option pricing, using the traditional Black-Scholes model as a benchmark. Relevant approaches demonstrate artificial neural networks trained to learn the Black-Scholes function, but very few works use market data to test the models. The majority use simulated or generated datasets for both training and prediction. In this work, we train the network using artificially generated data of around 6.5 million instances, and then we apply the testing in real market option data from thirty-five S&P100 stocks. So, testing data is not derived from the same distribution as training, and we can examine model performance in real market data, adding thus a unique contribution to existing research.

The structure of the paper is as follows. In the next sections, key background information for options and their pricing is presented. The Black-Scholes method is also presented briefly in the section along with key terminology of artificial neural networks. Several key relevant publications on machine learning models and their applicability in pricing are also discussed. In section three, we present the method and the datasets, followed by results and a discussion on findings. The work concludes with some discussion of the findings and next steps. Overall, the key outcome from the present work is that artificial neural networks can play a substantial role in option pricing, although further exploration and experimentation are needed to reach the required robustness and become less ad hoc and data-sensitive as a method.

2 Background

2.1 Options Basics

In general, an asset's present value is linked to its expected cash flow. However, some assets, called options, depend on underlying assets, derive their value from them, and their cash flows depend on the occurrence of specific events. So, the expected cash flows approach cannot be used to estimate their value. For this reason, alternative methods have been developed to price them fairly. Options are financial instruments used either for risk reduction and hedging or as investments following market trends of the underlying assets, [1].

An option is a contract between two parties for a specific quantity of an underlying asset, with an expiration date (maturity date). The holder of the contract has the right, but not the obligation, to buy or sell the specified quantity of the asset at a specified price (strike price), either at the maturity or earlier. If an option is exercised by the holder, it expires without any further obligation. Concerning the right to buy or sell the underlying asset, options are distinguished into call and put options.

Call options offer the right to buy a specified quantity of the underlying asset at the strike price, either on maturity or any time before. If the option is not exercised until the expiration date, it expires without any benefit or further obligation for the holder. The holder pays a price to purchase the option expecting a benefit if the price of the underlying asset is higher than the strike price. In this case, the holder exercises the option at strike price and buys the underlying asset at this price, instead of the higher market price. The difference is the gross investment profit. If the asset price is lower than the strike price at maturity or earlier, the option is not exercised. So, the net profit is the difference between the gross profit and the call purchase price, if the option is exercised.

Put options offer the right to sell a specified quantity of the underlying asset, at strike price, again either at maturity or earlier. A put option has a price paid by the investor who expects a profit in case the price of the underlying asset is less than the strike price of the option. If the underlying asset has a price lower than the strike price of the put option on maturity or before, the option is exercised and the option holder sells the underlying asset at a higher price compared to the market value, which comprises the gross profit of the investment. In case the underlying asset has a price higher than the strike price, the option is left to expire. The net profit again comprises the difference between the gross profit and the put option purchase price, [2].

Options can be also classified in terms of the exercise date or the underlying asset types. So, European options do not allow for exercise before maturity and the exercise date is defined in the option contract. American options, on the other hand, allow for exercise at any point of time before maturity and are more attractive for trading. Considering some fundamental asset types, options can be either stock options, stock index options, future options, or product options. Many more option types exist, but in this work, we focus on the two most known, the American and European ones.

2.2 Option Pricing Methods

The key idea behind option pricing is that options are traded in exchanges in mature markets, or specially organized exchanges in less developed markets. So, typically, at the initiation of an option contract, the buyer pays the option price (premium) to the option seller (writer). The premium defines the maximum profit the seller can receive from the transaction. Consequently, fair, and accurate option pricing is key for the efficiency of option markets. Following finance theory, the determinants of option price are the following:

- The current value of the underlying asset.
- The value variance of the underlying asset or volatility.
- The dividends of the underlying asset.
- The strike price of the option.
- The expiration date of the option or time to maturity.
- The risk-free interest rate during the option life.

Based on the above, a variety of pricing methods and variations have been introduced to price options accurately. The Black-Scholes model is the predecessor of all and since its introduction in 1973 remains the most influential, [3]. It offers an analytical method to estimate the theoretical arbitrage-free price of an option provided that some market parameters are known. Another widely used model is the Binomial which was introduced in 1978 and follows a discrete-time approach, [4].

Except for those two popular methods, many variations and novel approaches have been introduced, as the domain is very active and the stakes in the finance industry are very high. However, despite the introduction of more sophisticated methods, the traditional ones seem to outperform some comparative studies for American options, where analytical solutions cannot be generated, [5]. In the following, we review some representative works of artificial neural networks approaches in pricing, that use the Black-Scholes model as baseline.

2.3 Black-Scholes Model

The Black-Scholes model introduced by Fisher Black and Myron Scholes in 1973 is considered one of the most influential models in finance, [3]. It assumes that stock prices follow a random walk move and, for a market to be efficient, stock prices should not follow a pattern that could be predicted. If this assumption does not hold, stock future prices can be predicted and there could be financial gain. Since its introduction, there have been many variations, but in its initial version there is no dividend until the option maturity date, no transaction fees are charged, and the risk-free rate and volatility are known constants.

The model is parametric and its famous formula for the arbitrage-free price of an option can be used to price options as a function of current stock or underlying asset price, option strike price, option time to maturity or expiration, risk-free rate and volatility of the underlying stock return. The formula for call option price is the following:

$$C = S * N(d_1) - K * \left(e^{-r_f}/_T\right) * N(d_2) \qquad (1)$$

with

$$d_1 = \frac{ln\frac{S}{K} + \left(r_f + \frac{\sigma^2}{2}\right) * T}{\sigma\sqrt{T}} \qquad (2)$$

$$d_2 = \frac{ln\frac{S}{K} + \left(r_f - \frac{\sigma^2}{2}\right) * T}{\sigma\sqrt{T}} \qquad (3)$$

The formula for the put option price is:

$$P = K * \left(e^{-r_f}/_T\right) * N(-d_2) - S * N(-d_1) \qquad (4)$$

where:

- C: the price of the call option
- P: the price of the put option
- S: the current price of the stock or underlying asset
- N(d): the cumulative normal probability density function
- K: the strike price of the option
- σ: the volatility of the stock or underlying asset
- T: the time to expiration of the option
- r_f: the risk-free interest rate

Several adjustments have been proposed to the initial model to account for limitations that do not hold for all options. The model is widely used and referenced in almost every option pricing related work, and interested readers can find a decent review of the work of Hull among others, [6].

2.4 Artificial Neural Networks

Artificial neural networks were initiated back in 1943 by the work of McCulloch and Pitts, where the idea was to use mathematical formulation on the concept of a biological neuron to be able to execute computations mimicking brain neurons' functionality. In the past decades, there has been exponential research developments, driven mainly by big data and computing power evolution in the past decade. Applications were so successful, that we can find numerous domains which utilize the power of artificial neural networks and deep learning models. A groundbreaking work that set the ground for further developments was the universal approximation theorem, which proves that an artificial neural network can approximate any continuous function in a closed interval based on input variables. The importance of the theorem is quite high as, based on it, we can use an artificial neural network, even with one hidden layer, to model any complex non-linear relationship, [9]. This is a key benefit of artificial neural network models, as most real-world problems cannot be modeled and solved analytically.

A domain where complexity and non-linearity are combined with real-time transactions and stochastic processes, and where mathematical modeling is not feasible, is derivatives markets. Under some abstractions and limitations, we can model analytically, but again not all problems can be solved. Option pricing is an example of a key problem for the financial industry, that can partially be modeled by parametric methods and solved analytically. Black-Scholes variations and Monte Carlo simulation are the key parametric traditional methods. However, following the advent of data and artificial neural networks, researchers in the nineties proposed alternative nonparametric approaches based on machine learning. They were among the first researchers to study a data-driven approach and propose the utilization of artificial neural networks for option pricing, [10]. Those initial approaches opened a new research direction for financial derivatives pricing using machine learning methods. Some early works reported a quite high level of accuracy, [11], [12], followed by recent works with rich analysis and benchmarking, [7], [8]. As the number of works in machine learning-based option pricing is increasing, not all researchers agree to positive results. Controversy on whether artificial neural networks outperform compared to traditional methods and in what settings is still under research. Usually, works were based on plain neural network architectures and limited data, so reported weak results for neural networks compared to Black-Scholes, something expected as neural networks require large training datasets. Also, some researchers claimed that results differ if we examine options in the money out of the money, or other factors. However, an increasing corpus of papers agree on the high level of neural network accuracy for option pricing compared to traditional models.

It is important to mention though that in all works the Black-Scholes model is still used as a benchmark to test for errors in pricing. So, despite the promising performance of artificial neural networks, theoretical models are still dominant. However, the research direction is towards developing neural network architectures that can offer increased accuracy.

3 Data and Methods

This work aims to explore the accuracy level of neural network architecture for call option pricing estimation using empirical data for testing. The approach we followed is to:

- use a multilayer perceptron network architecture,
- train it using artificial data generated from the Black-Scholes formula, which is considered a benchmark method for all option pricing methods, and next,
- test the network in real call options market data for a portfolio of thirty-five stocks randomly selected from the S&P 100.

The key research question that we explore is how well an artificial network performs in real market data when trained with synthetic data. This work builds on some related works, [13], [14], however it examines real testing data, instead of artificially generated. Our approach examines the case that testing data, that a neural network is going to use for prediction, does not follow the same distribution as the training data. In similar works, we see that the performance of multilayer perceptron networks in option pricing is quite high, using artificial data for both training and testing, something that is expected, in general. So, we learn the Black-Scholes with artificial data and test the accuracy in real data.

The approach we followed comprises the phases below:

- Generate artificial call options data using the Black-Scholes formula for a range of realistic values.
- Define a multilayer perceptron model with initial parameters.
- Train the model with the artificial dataset.
- Validate the model with a subset of the artificial dataset.
- Collect real market data for call options for thirty-five randomly selected S&P100 stocks.
- Test the model with the real market dataset.
- Evaluate the model using the real market data as the benchmark.

The entire work for the data, both the generation of artificial data and collection of market data, was executed by specific modules developed in Python

3.11, [15]. The multilayer perceptron was implemented in Python, using the Keras library and Tensorflow as the computational engine. For the computations, a typical desktop computer was used with Intel Core i5 at 2.90 GHz and 8GB RAM.

3.1 Training Dataset

The training dataset was generated with artificial data using the Black-Scholes formula for a range of values, replicating many call options. Even though in real trading call option prices deviate from the Black-Scholes formula, it is a baseline method to calculate option prices formally. For this work, we generated around 6.5 million call option prices in total, with the process taking 19 minutes of CPU time. For the generation, we used stock price values ranging between 10 and 200 USD, with strike prices as a multiple of stock prices to avoid extreme values. So, strike prices range between 10 and 300 USD. The volatility was selected between 10% and 60% with a step of 5%, and the risk-free rate was ranging between 1% and 2%. Finally, the time to maturity was selected between 0.1 and 1 year. In Table 1 the values for the training set are summarized.

Table 1. Parameters for the 6.5m call option prices artificial dataset.

Parameter	**Range**
Strike price (K)	0-290 (USD)
Dividend rate (q)	0%
Volatility (a)	10%–60%
Stock price (S)	10–200 (USD)
Maturity (T)	0.1 to 1 year
Risk-free rate (r)	1%–3%

The distributions of the generated call prices and the strike prices are depicted below for reference (Figure 1, Figure 2). The stock prices follow a uniform distribution, while the strike prices and the call prices are right-skewed. Even if the dataset is artificial, as soon as the objective is to learn the Black-Scholes formula, the call price is generated in the dataset by the actual Black-Scholes formula, and this is used in the training phase from the artificial neural network to learn the formula.

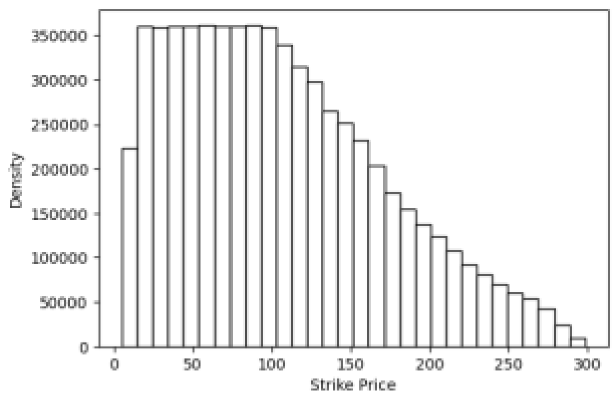

Fig. 1: Artificially generated strike price distribution

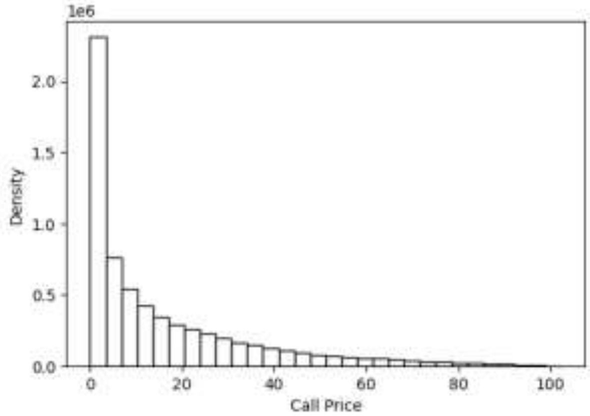

Fig. 2: Artificially generated call prices distribution

3.2 Testing Dataset

For the testing phase, we utilized data originated from publicly available market data for thirty-five randomly selected S&P 100 stocks. As market data do not strictly follow the theoretical calculations, and on the other hand include some extreme values that are not met in practical trading, we performed several adjustments. In total, 3,500 records were collected. The decisions taken for data preparation are the following:

- The stocks selected are a random subset of S&P 100 stocks, to include more diverse data, instead of picking based on some criterion, like revenues or market capitalization.
- Stock prices refer to the closing price of the previous day. We compared the closing prices with the ask and the average of the bid and ask, and we did not see deviations, so we kept the previous closing price.
- Dividend was collected from market data as provided (forward dividend and yield).
- For the implied volatility we used the market-provided volatility, as the mean value over the last 30-day period, derived from the average of the put and call implied volatilities for options

with the relevant expiration date, based on market data.

- We focused on call options, but the same analysis can be applied to put options.
- We selected in-the-money call options.
- We filtered the data, excluding not realistic and non-representative observations from the data to obtain more meaningful results.

Some further filtering was applied, as followed in other works, [13], [14], to exclude nonrealistic and non-representative observations. Some very high option prices were excluded to avoid large deviations between theoretical and observed option prices. The distributions of the call and strike prices for the dataset are depicted below (Figure 3, Figure 4, Figure 5). The stock prices vary while the strike prices and the call prices are right-skewed, in a similar way to the artificial dataset. Also, we calculated the theoretical call option prices using the Black-Scholes formula to use them as a benchmark. In general, it seems that even if the market data can be considered they depart from the theory, the distributions are not substantially different from the artificial data.

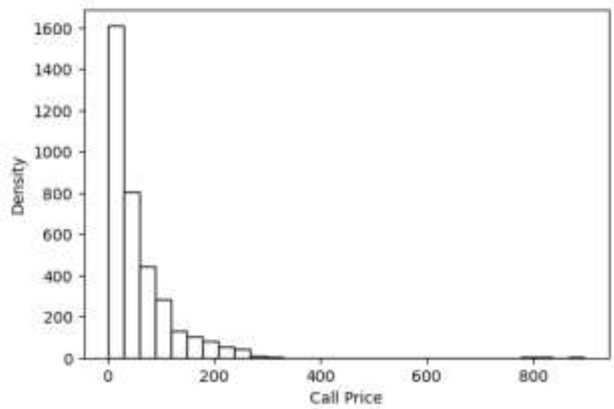

Fig. 3: Market collected call prices distribution

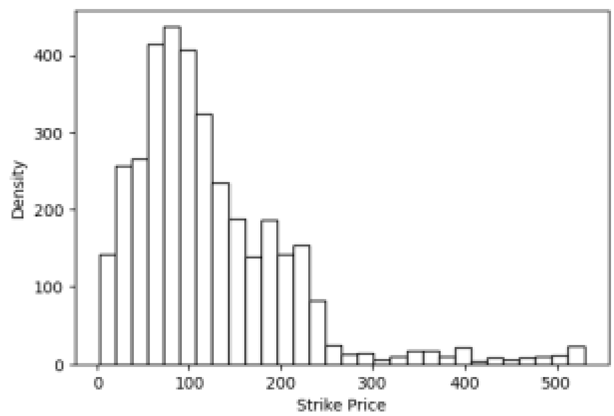

Fig. 4: Market collected strike prices distribution

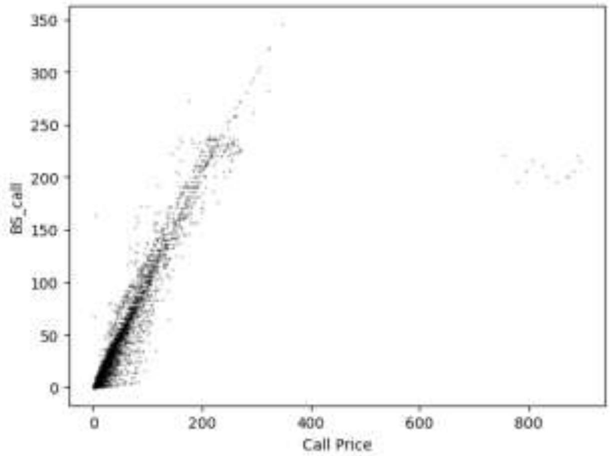

Fig. 5: Actual call prices versus theoretical BS calculated

3.3 Artificial Neural Network

For the artificial neural network, we selected the architecture of a multilayer perceptron (MLP), as a commonly used approach for such works and it also fits well in finance settings.

The model was trained using the entire set of parameters as input features:

- strike price,
- stock price,
- risk-free interest rate,
- time to maturity, and
- volatility,
- and the call price as the output.

Following some similar approach, the input variables were normalized, [10]. After some experimentation, we used a network with one input layer, three hidden layers of 120 neurons each, and one output layer for the call option price output. The first and the third hidden layers utilize the Elu activation function and the second the Relu activation function. The model was trained using the artificial dataset of 6.5m instances, split into 80% subset used as training sample and the remaining 20% used as validation sample. The test was performed on the real market dataset and not the synthetic one, where the performance of the model was evaluated. The model hyperparameters were tuned to a 25% dropout rate, a rule-of-thumb dropout rate to prevent overfitting. The number of epochs used for training was 100 and the batch size (the number of samples processed before updating the model) was set to 64. Finally, the loss function was optimized using mean square error (MSE).

4 Results and Discussion

The key research question in this work is to explore the accuracy of an artificial neural network in estimating option prices on real market data, having been trained with artificial data originating from the Black-Scholes formula. The approach we followed was to test the model on a random set of S&P 100 stocks and their market-based option data after we had trained it and tuned the hyperparameters with synthetic data. For both training and testing we utilized Python tailor-made libraries along with the Tensorflow module, [15]. The set of tuned parameters was exported into a file that was used in all testing scenarios using the market dataset. We focused on in-the-money call options, but the same approach can fit at out-of-the-money options.

The results from the testing phase of the model are presented in Table 2, and the normalized predicted call prices against the actual ones are depicted in Figure 6. As we can see, the Root mean square error is equal to as low as 06560. Also, from the histogram (Figure 7) of the differences between actual and predicted call prices, we can see that the error is very small in general.

Table 2. Testing Error Results with Market Data

Mean Squared Error:	0.004304196575715178
Root Mean Squared Error:	0.0656063760294316
Mean Absolute Error:	0.04031098310438521
Mean Percent Error:	0.22251207590972308

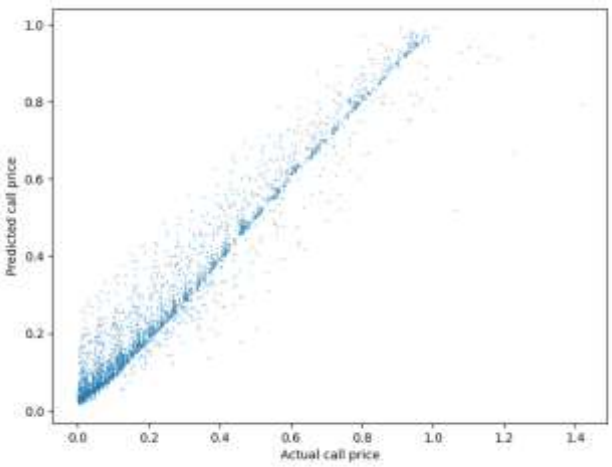

Fig. 6: Predicted call prices against actual ones

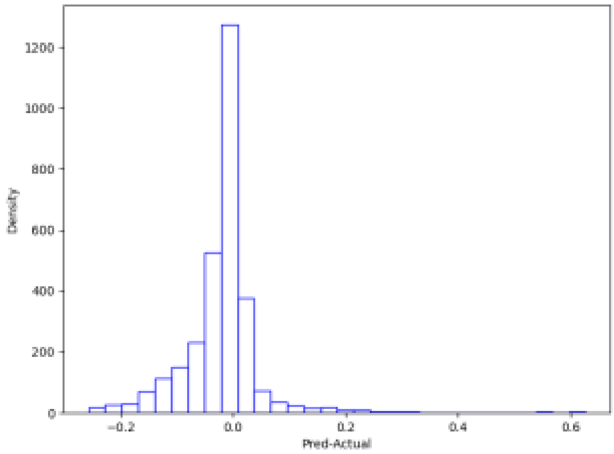

Fig. 7: Histogram of difference between predicted and actual prices

To check model accuracy, we performed additional testing with the market dataset, but we replaced call option price, as the output variable, with the value calculated from the Black-Scholes formula. Even if the market price is not identical to the calculated one, as shown previously, it can be used as a benchmark.

So, for the in-the-money call options, the results are presented in Table 3, and the normalized predicted call prices against the real ones are depicted in Figure 8. As we can see, the Root mean square error is as low as 0.0284 that is comparable to the market dataset, and from the histogram (Figure 9) of the differences between actual and predicted call prices, we can also see that the error follows the same pattern as in the network.

Table 3. Testing Error Results with BS prices

Mean Squared Error:	0.0008069991156531251
Root Mean Squared Error:	0.028407729857437l3
Mean Absolute Error:	0.02018331088989721
Mean Percent Error:	0.06679347660794391

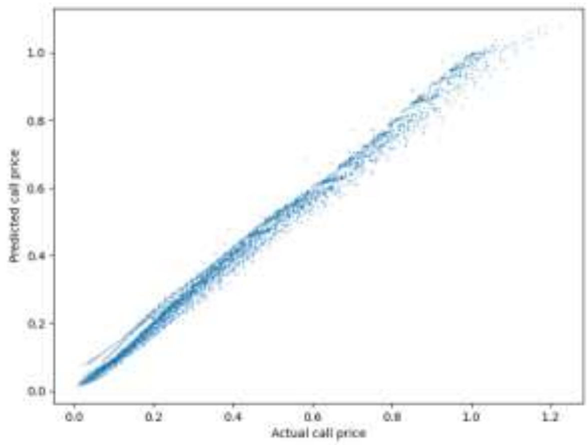

Fig. 8: Predicted call prices against actual ones

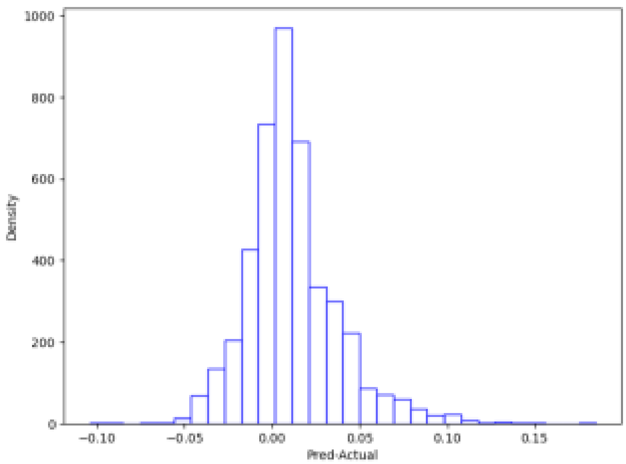

Fig. 9: Histogram of the difference between predicted and actual prices

So, overall, we can claim that the model, even in a preliminary setting, is comparable to the Black-Scholes formula for calculating option prices at market data and can evaluate options in acceptable accuracy. Provided that market prices are not strictly derived from the Black-Scholes formula, it is reasonable to assert that the level of error is within reasonable limits. Some additional experiments can be performed including put options and combining variations of volatility estimations for both in and out-of-the-money options. Also, the trained model can be benchmarked to various alternative machine learning models in terms of accuracy and computational performance.

5 Conclusion

In this work, we explored the accuracy of an artificial neural network on call option pricing using real market data for testing and artificial option pricing data for training. We used a multilayer perceptron model, a large synthetic dataset for training, generated from the Black-Scholes formula, and a real market dataset, comprising thirty fine randomly selected S&P 100 stocks. As the baseline for pricing errors and estimations in the study, we used the Black-Sholes model. From the results, we can see that a multilayer perceptron is capable of learning the BS function accurately using synthetic data and estimating prices for options with a high level of accuracy, competitive with the Black-Scholes formula.

Other relevant works using artificial neural networks conclude in similar results, however, this work adds the experimentation of using actual market data. Provided that the model is not static, but it can be retrained using additional data, including mixed artificial and actual data, its accuracy can be increased, and it can become more valuable for practitioners, who might select machine learning paradigms for option pricing in various assets and markets. Some limitations in this work include the training sample, the specific network architecture, and the limited focus on S&P 100 stock options. As artificial neural networks are data-driven, developing appropriate training datasets is critical for their performance, so there is a need for diverse training datasets. Also, in this work, we did not proceed to feature engineering or advanced sampling for the training, something that can be examined further in subsequent works. In addition, alternative network architectures can be tested or further experimentation with hyperparameters can be performed, and focus can be expanded to additional assets. In the future, we plan to develop training processes using market data from a variety of sources.

Despite the limitations, it is evident that machine learning models can be used by practitioners as main or alternative methods for option pricing, however, it is necessary to build appropriate user-friendly software solutions to deploy similar machine learning models on web environments or mobile phone settings. This work, and any future contributions, aim to the development of this fast evolving area.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)
The author developed the present research in its entirety.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself
No funding was received for conducting this study.

Conflict of Interest
The authors have no conflicts of interest to declare.