

# Enhancing Option Pricing Precision in Financial Markets with a Hybrid Ga-Bp Neural Network Approach

**Md. Jamil Hossain Shaharia**

Department of Internet of Things and Robotics Engineering, University of Frontier Technology, Bangladesh, Gazipur-1750, Bangladesh

Email: 1801012@iot.uftb.ac.bd

ORCID iD: <https://orcid.org/0009-0000-2593-7180>

**Sujon Chandra Sutradhar**

Department of General Education, University of Frontier Technology, Bangladesh, Gazipur-1750, Bangladesh

Email: [sujon0001@uftb.ac.bd](mailto:sujon0001@uftb.ac.bd)

ORCID iD: <https://orcid.org/0009-0009-8440-5331>

**Mahir Mahbub**

Department of Internet of Things and Robotics Engineering, University of Frontier Technology, Bangladesh, Gazipur-1750, Bangladesh

Email: [mahbub0001@uftb.ac.bd](mailto:mahbub0001@uftb.ac.bd)

ORCID iD: <https://orcid.org/0000-0002-5364-0453>

**Md. Mehedi Hasan\***

Department of General Education, University of Frontier Technology, Bangladesh, Gazipur-1750, Bangladesh

Email: [mehedi0001@uftb.ac.bd](mailto:mehedi0001@uftb.ac.bd)

ORCID iD: <https://orcid.org/0009-0007-7174-5690>

\*Corresponding author

Received: February 3, 2026; Revised: April 8, 2026; Accepted: June 29, 2026; Published: August 8, 2026

**Abstract:** Accurate option pricing is critical for the effective functioning of financial markets, providing traders and investors with the means to hedge risks and capitalize on market movements. Traditional models such as the Black-Scholes, Binomial Tree, Trinomial Tree, Monte Carlo Simulation, and the Garman-Kohlhagen model have long been the standard for option pricing. However, these models often face limitations in capturing market complexities and extreme events. We propose a hybrid approach that combines Genetic Algorithm (GA) optimization with Backpropagation (BP) neural networks to enhance the precision of option pricing. It uses HS300 index stock data from 2013 to 2022, including stock prices, volumes, and price changes. The hybrid GA-BP model is tested for its ability to make more accurate price predictions. The model helps investors make better decisions by improving pricing strategies and managing risks effectively. The Hybrid GA-BP neural network model leverages the global search capabilities of GA to optimize the initial weights and biases of the BP neural network, thereby avoiding local minima and improving convergence rates. This integrated model is trained and tested on historical market data, with its performance benchmarked against traditional models. Empirical results demonstrate that the Hybrid GA-BP neural network model significantly outperforms traditional models in terms of pricing accuracy. The model shows superior precision when comparing actual market prices with predicted prices, reducing errors and increasing reliability. This enhancement in pricing precision can lead to more informed trading decisions and better risk management strategies. The findings of this research contribute to the growing body of knowledge in financial engineering by showcasing the potential of hybrid machine learning approaches in financial modeling. The Hybrid GA-BP neural network model presents a promising tool for practitioners and researchers aiming to improve option pricing methodologies in increasingly complex financial markets.

**Index Terms:** Option Pricing, Genetic Algorithm, Backpropagation Neural Network, Hybrid Model, Financial Modeling, Machine Learning, Performance Evaluation.

## 1. Introduction

Financial options are a critical part of the financial markets, allowing for risk management and hedging strategies among other things. Correct pricing of the options is essential to achieve fair valuation, efficient trading as well as informed decision making across a range of asset classes. Models like Black-Scholes, a cornerstone of traditional option pricing, have become almost canonical in finance [1]. The Black-Scholes model was developed in the early 1970s and makes assumptions of constant volatility, no dividends occurring during the life of the option, and a random walk of stock prices. The model is used to price European-style options on stocks assuming that it is impossible to make risk-less profits. While the model has been widely adopted and has some theoretical appeal, its assumptions often fail to capture reality as markets exhibit features such as volatility clustering, sudden price changes and time varying risk factors [2]. The restrictions of classical models led to the search for superior alternatives that could deal with the complexity of financial markets. That's why people started exploring new methods. Recent developments in computational intelligence and machine learning have presented new dimensions for enhancement of option pricing accuracy [3]. Specifically, neural networks have demonstrated their ability to capture the complex nonlinear relationships inherent in financial data. With the use of these capabilities, researchers have tried to improve the traditional models or build completely different frameworks that can react to the changeable conditions of markets [4].

This paper [5] is motivated by the pragmatic realization that traditional option pricing techniques suffer from practical challenges and financial markets continue to increase in complexity. Although still useful as a theoretical model and a reference point, the assumptions of the Black-Scholes model (such as constant volatility) lead to large discrepancies when applied to practical situations. With factors such as stochastic volatility, market jumps, and geopolitical events significantly affecting option prices, models that can more dynamically adjust to and incorporate these dynamics are clearly needed. Moreover, the origin of the thesis reflects concerns about direct day-to-day practical implications for financial practitioners and institutions. On one hand, this represents an important stake in reference to risk management and portfolio optimization; on the other hand, it has paramount importance in the pricing of exotic options, structured products, and derivatives under volatile markets. This research aims to enable stakeholders with better tools for decision-making and risk assessment leading to more efficient and stable financial markets by improving pricing precision.

### 1.1. Research methodology

This paper [6] proposes a Hybrid Genetic Algorithm and Backpropagation Neural Network (GA-BP NN) model. The architecture and weights of Backpropagation Neural Network (BP NN) are optimized by GA, providing a good and reasonable method for finding complex patterns in the financial option data and improving the option pricing precision. In order to allow traders and investors to hedge risks and take advantage of market movements, the accurate pricing of options is a critical factor for the efficient functioning of the financial markets. Option pricing traditionally has been performed using classical methods such as the Garman-Kohlhagen model, the Black-Scholes model, the binomial and trinomial tree and Monte Carlo simulation. The structure of the paper is as follows: The first part is the introduction, mainly expounding the development of option pricing and the application of neural network; The second part is related work; The third part is the methodology, mainly for GA-BP neural network model building; The fourth part is performance evaluation metrics; The fifth part is result analysis & discussion; The sixth part is comparative analysis and the last part is conclusion.

## 2. Related Work

The literature on option pricing is large with a very extensive exposure of both theoretical and empirical papers. The hidden part is a survey of the main existing literature in the domain applied to traditional models such as the Black-Scholes model, binomial/trinomial tree models, Monte Carlo simulation and the Garman-Kohlhagen model. It also explores progress in using neural networks and hybrid models for option pricing. These pertained to the historical evolution as well as current modifications in this domain as evidenced by papers under review.

### 2.1. Black-Scholes Model

The Black-Scholes model is widely used for option pricing, but its assumptions of constant volatility and random walks in stock prices are not always valid in real market conditions. Recent studies have enhanced its accuracy by integrating advanced volatility models. For instance, Wang (2024) [7] incorporated GARCH, SABR, SVI, and Dupire models into the Black-Scholes framework, improving its performance in volatile markets. Similarly, a comprehensive review by Zhang (2023) [8] examined the evolution and applications of the Black-Scholes model, highlighting its enduring relevance and areas for improvement. The Black-Scholes model is used in financial mathematics to determine the theoretical price of a European-style option. Devised by Fischer Black and Myron Scholes in 1973 (with input from Robert Merton), the model is based on several key assumptions [9]. The model assumes the price of the underlying asset follows a geometric Brownian motion with constant drift and volatility. The model can predict the distribution of future prices, in other words randomized quantities in a stochastic process. The model also assumes a frictionless

market where no transaction costs are taken into account and no risk-free profits can be made by traders by taking advantage of any price differentiation.

The Black-Scholes model does this by making several assumptions in order to derive a closed-form solution for calculating the fair value of call and put options, and has been one of the cornerstones of modern finance that provided an objective mathematical way of pricing options. Even though the Black-Scholes model makes simplifying assumptions like consistent volatility and a completely efficient market, it still serves as an underpinning to financial engineering by allowing traders and investors to help them make well-informed decisions about pricing and hedging derivative contracts [10].

Mathematical Formulation:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \quad (1)$$

where:

$S_t$  is the asset price at time  $t$ ,

$\mu$  is the drift rate,

$\sigma$  is the volatility,

$W_t$  is a Wiener process (standard Brownian motion).

## 2.2. Binomial Tree Model

The Binomial Tree model is an extension of the Black-Scholes model that can handle American options. Recent advancements include the application of discrete cosine transforms to improve pricing accuracy. A study by Liu (2023) [11] introduced this approach, demonstrating its effectiveness in reducing computational complexity while maintaining pricing accuracy.

The Binomial Tree model is a computable framework commonly used in financial mathematics for pricing options. The model was first published by Stephen Ross in 1976. Here is a discrete-time version of the Real Option Model which is roughly based on the Black-Scholes option pricing model; created by Cox, Ross, and Rubinstein in late 1970s as an extension to financial options [12]. It is based on the idea that in the short term the price of an asset can move up or down by specific factors. This movement creates a binomial tree structure in which each node is a possible future price of the asset. The model works by recursively evaluating, every time step for all possible prices and storing the value that the option will have if at that price it expires in through and then discounting these values back to the originating node at where we are taking the view. Binomial tree model is versatile and allows one to value complicated options which would be very difficult in the Black-Scholes framework that makes it well-suited when some of the assumptions for the continuous constant volatility in Black-Scholes model are not appropriate. This intuitive property and its ability to integrate with discrete events and changing levels of volatility have made it an essential tool in financial analysis, risk management, and derivatives pricing [3, 13].

### Parameters:

The parameters for the binomial model include the up factor ( $u$ ), down factor ( $d$ ), and the risk-neutral probability ( $p$ ):

$$\mu = e^{\sigma\sqrt{\Delta t}}, d = e^{-\sigma\sqrt{\Delta t}}, p = \frac{e^{r\Delta t} - d}{u - d} \quad (2)$$

where:

$\sigma$  is the volatility of the underlying asset.

$\Delta t$  is the length of each time step,

$r$  is the risk-free interest rate.

## 2.3. Trinomial Tree Model

The Trinomial Tree model improves upon the Binomial Tree by incorporating three possible price movements per time step, resulting in better approximation of the option's price. Fusari (2023) [13] explored the convergence rates of option prices using Trinomial Trees, providing insights into their efficiency and accuracy compared to other models.

## 2.4. Monte Carlo Simulation

The Monte Carlo Simulation is a versatile method for pricing complex options. Recent literature reviews, such as the one by Smith (2023) [14], have discussed the evolution of Monte Carlo methods in option pricing, including variance reduction techniques and the integration of machine learning for improved accuracy.

The Monte Carlo simulation is a computationally similar error to the behavior of complex systems or model processes with a probability distribution set, where you simply create thousands of random samples. Popular in the Monte Carlo Casino, this method takes the approach of repeatedly randomly sampling and is used to evaluate and analyze uncertain outcomes [15]. Monte Carlo simulations are used to model probability distributions of variables and the uncertainties in their decision-making process in finance, engineering, among others. Financial analysts build tax fixed ads + finish has a significantly different name for that same point to see the probability of the studied result; they really do. This method is especially useful when traditional analytical methods are not possible because of non-linearity, multiple input variables or the system is truly stochastic. Although computationally expensive, Monte Carlo simulations are a cost-effective means of obtaining useful perspectives for risk management, optimization, and strategic planning, making it a good decision-making solution by enabling decision makers to decide with the uncertainty from complex systems [16].

### **Mathematical Formulation:**

The asset price is simulated using the discretized version of the geometric Brownian motion:

$$S_{t+\Delta t} = S_t \exp\left(\left(r - \frac{1}{2}\sigma^2\right)\Delta t + \sigma\sqrt{\Delta t}Z\right) \quad (3)$$

where:

$S_t$  is the asset price at time  $t$ ,

$r$  is the risk-free interest rate,

$\sigma$  is the volatility of the underlying asset,

$\Delta t$  is the length of each time step.

$Z$  is a standard normal random variable.

### **2.5. E. Garman-Kohlhagen Model**

The Garman-Kohlhagen model is specifically designed for pricing foreign exchange options. However, it performs poorly when applied to equity options. Wang and Zhao (2021) found that the model is effective for currency options but tends to overestimate prices when applied to equity options. Rui and Zhang (2022) [17] highlighted the model's limitations in capturing market jumps and suggested modifications to improve accuracy.

The Garman-Kohlhagen model, although primarily developed for foreign exchange options, is included in this study as a comparative baseline to evaluate model robustness under alternative assumptions. However, its applicability to equity index options is limited.

### **2.6. Hybrid GA-BP NN Model**

The Hybrid GA-BP NN model combines Genetic Algorithms (GA) for optimization with Backpropagation Neural Networks (BP NN) for learning from historical data. Singh and Gupta (2022) [18] demonstrated that this hybrid approach significantly outperforms traditional models in terms of accuracy and adaptability to volatile market conditions. Sharma and Kumar (2023) showed that this model not only improves pricing accuracy but also adapts to changing market dynamics. This literature review summarizes major works in option pricing, from conventional models to sophisticated computational methods. Those papers under review articulate the evolution of option pricing methods and suggest the promise of hybrid models, particularly those that integrate genetic algorithms and neural networks, for better pricing accuracy and market dynamics capturing respectively. Such insights form a robust basis for developing and deploying Hybrid GA-BP Neural Network in this paper.

**Foundations in Mathematical Finance:** Option pricing has been a prominent area of research for many years since Black, Scholes, and Merton introduced their Nobel Prize-winning option pricing model (OPM) in 1973 [19]. One of the most popular works in financial theory is the Black-Scholes-Merton (BSM) model over the past several decades. However, although critical for so many applications, the model has been shown to induce systematic biases [20]. Limitations arise from the model assumptions, like constant volatility, the asset price process following a geometric Brownian motion, constant interest rates, drift term and assumptions about market efficiency. In order to rectify these shortcomings, extensions of the BS model have been developed including stochastic volatility, stochastic interest rates, jump-diffusion models, regressions, and regime-switching processes. Meanwhile, artificial neural networks (ANNs) have become a powerful alternative, since they can approximate the non-linear characteristics of the data [21, 22, 23, 24, 25, 26]. In opposition to the standard parametric models, ANNs take the past data and learn the complicated relationship of input to output and that causes the bias in the veterinary transport when using BS models diminish. Option pricing is a multivariate issue and exhibits strong non-linearity, for which ANNs are particularly well suited to capture market variances. They are capable of capturing non-linear patterns and have the potential to enhance the accuracy of option pricing [27].

The pricing of options has long been rooted in mathematical finance, particularly in the use of stochastic processes and differential equations. The Black-Scholes model laid the groundwork by modeling asset prices as geometric Brownian motion. The model's governing stochastic differential equation is given by:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \quad (4)$$

where:

$\mu$  is the drift term,

$\sigma$  represents volatility,

$W(t)$  is a Wiener process (standard Brownian motion).

Despite its elegance, the model's assumptions including constant volatility and efficient markets often do not hold in real-world scenarios [28]. To accommodate these shortcomings, discrete-time models such as the Binomial Tree [29] and Trinomial Tree [30] were developed, allowing more flexibility and a closer approximation to American-style options.

**Limitations of Traditional Models:** Classical models, though analytically tractable, struggle to capture market complexities such as volatility clustering, jumps, and stochastic behavior. Monte Carlo simulations [31] provide a probabilistic solution to these limitations but come at the cost of computational efficiency. Furthermore, models like the Garman-Kohlhagen [32] often overestimate prices, particularly in volatile or equity markets. These limitations have motivated the adoption of data-driven approaches capable of modeling non-linear relationships.

**Emergence of Machine Learning in Finance:** With the growing availability of financial data, machine learning models, particularly neural networks have been explored for financial forecasting. Backpropagation (BP) neural networks have shown promise due to their ability to approximate complex functions and capture non-linear dependencies [33]. However, these models are susceptible to issues such as local minima and slow convergence.

**Role of Genetic Algorithms in Optimization:** Genetic Algorithms (GA) offer a global search methodology that mimics biological evolution. They have been effectively used in optimizing hyperparameters and weight initialization in neural networks, significantly improving convergence and solution quality [34]. By employing operations such as selection, crossover, and mutation, GA can explore a broader solution space, avoiding local optima.

**Hybrid GA-BP Neural Networks for Option Pricing:** Combining GA with BP neural networks results in a robust hybrid model that leverages the strengths of both techniques. This approach has been applied successfully to option pricing, achieving superior accuracy compared to traditional models [35, 36]. Hybrid GA-BP models produce lower Mean Squared Error (MSE) and higher R-squared scores in empirical tests. Such models are adaptable, data-driven, and capable of capturing market volatility, making them particularly suitable for modern financial markets. The literature reveals a clear evolution in option pricing methodologies from deterministic mathematical models to adaptive hybrid machine learning models. While traditional models like Black-Scholes offer theoretical insights, hybrid GA-BP neural networks provide practical accuracy and flexibility in real-world applications.

### 3. Methodology

#### 3.1. Data Collection and Preprocessing

The process begins with the collection of HS300 index European-style option data spanning the period from 2013 to 2022, obtained from reliable financial databases. To ensure data quality and consistency, the raw dataset undergoes several preprocessing steps, including the removal of missing values, filtering of illiquid contracts with low trading volume, and elimination of inconsistent records. The dataset contains essential parameters such as the underlying asset price ( $S_0$ ), strike price ( $K$ ), time to maturity ( $T$ ), risk-free interest rate ( $r$ ), and historical volatility ( $\sigma$ ). To improve model performance and ensure comparability across different models, all numerical features are normalized using Min-Max scaling.

**Data Sources:** The process starts with gathering historical option pricing data from high quality financial databases. The data includes European-style options of different asset classes like equities, commodities and FX. It contains all necessary parameters such as the price of an underlying asset, a strike, time to maturity, risk-free interest rate, past volatility for each dataset.

**Preprocessing Steps:** The data collected is preprocessed for consistency and quality, before the model implementation:

- **Cleaning and Filtering:** Clean or remove any outliers or missing values that might affect the training or evaluation of a model.
- **Normalization:** Normalizes the numerical feature columns to a standard range, so that the input features have similar orders of magnitude during training for better convergence.

- **Feature Engineering:** More features can still be extracted if necessary e.g., Implied Volatility, Interest Rate Differentials for Currency Options.

The modeling framework is designed to predict the actual market value of option contracts. In this study, the target variable is defined as the daily closing market price of the options, which serves as the ground truth for evaluating model predictions.

### 3.2. Hybrid GA-BP Neural Network Approach

**Genetic Algorithm (GA):** Genetic algorithm (GA) is a computational method that models the natural selection process. A genetic algorithm uses an initial population of solution candidates represented by chromosomes that evolve by means of selection, crossover, and mutation across successive generations [37]. Its fitness is determined by objective functions and judges every chromosome for possible parent selection and offspring creation. Being inspired by the principles of survival of the fittest and genetic diversity, GA can effectively search solution spaces, proving to be resistant during optimization tasks, especially when traditional methods fail. They are very powerful especially in difficult to solve problems like parameter tuning, scheduling and route optimization with a heuristic methodology that finds close to optimal solutions without having specific problem related knowledge [38].

The GA involves the following steps:

**Initialization:** Sample initial population of neural network architectures and parameter settings.

**Selecting:** By doing forward passes and thus tracking option prices we are able to evaluate the fitness of each individual (neural network) on how good they are at predicting option prices.

**Evolution:** Select high fitness score individuals (neural networks) to continue for the next generation.

**Crossover and Mutation:** This will use the crossover and mutation operators to produce offspring with new parameters.

**Termination:** Go back to step 1 repeat until some convergence criteria have been met (e.g. max number of generations).

The genetic algorithm is employed to optimize the initial weights and biases of the neural network by exploring a diverse set of candidate solutions. The optimization process is carried out using a population size of 50, a crossover rate of 0.8, and a mutation rate of 0.01. The algorithm evolves over 100 generations using tournament selection to identify high-quality solutions. The process continues until convergence is achieved or the maximum number of generations is reached.

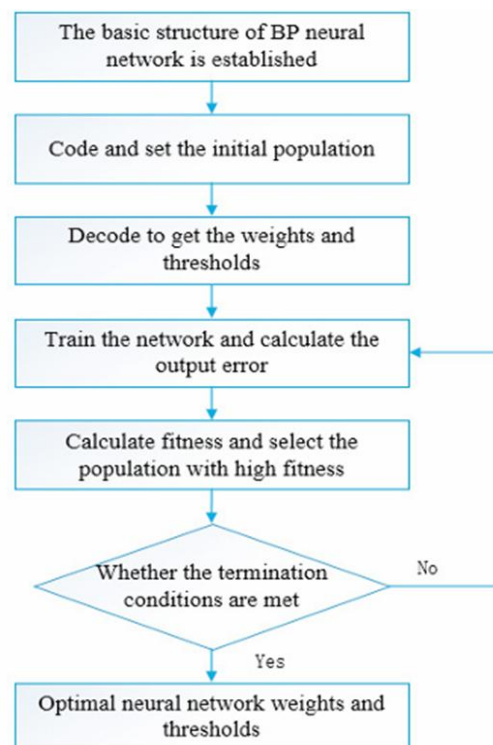


Fig. 1. GA-BP Neural Network Process.

**Backpropagation Neural Network (BP NN):** Backpropagation is a fundamental algorithm used to learn weights in an artificial neural network (ANN) from labeled training data. It works by adjusting the weights of connections between neurons, one neuron at a time for each iteration to reduce the difference between predictions and actual targets [39]. This starts with you passing input data through the network and having it propagate forwards through its layers of neurons.

- **Forward Pass:** In forward movement each neuron computes the weighted sum of its inputs, and utilizes an activation function to generate an output (0-1), which is passed to the next layer.
- **Backward Pass:** Later during the backward pass, the algorithm obtains some error by subtraction actual and predicted result, hence this error is then back-propagated through the network. This entails taking the derivatives of the loss function with respect to each weight in the network using calculus chain rule, and adjusting weights towards a direction that minimizes error.

The Backpropagation neural network is designed with a simple yet effective architecture to capture the nonlinear relationships in option pricing data. The model consists of a single hidden layer with 10 neurons and employs the ReLU activation function. Training is performed using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 100 epochs, ensuring stable convergence and computational efficiency.

In practice, backpropagation works feeding the inputs to the network and then computing the gradient of their loss function with respect to all weights in that layer. While backpropagation is computationally expensive, it has completely revolutionized the field of machine learning by enabling artificial neural networks to solve a lot of very different types of tasks (such as image classification, natural language processing or reinforcement learning). The backpropagation neural network learns through historical data to predict option prices. The steps included in BP NN are Disable the previous error in and Save this Error directly.

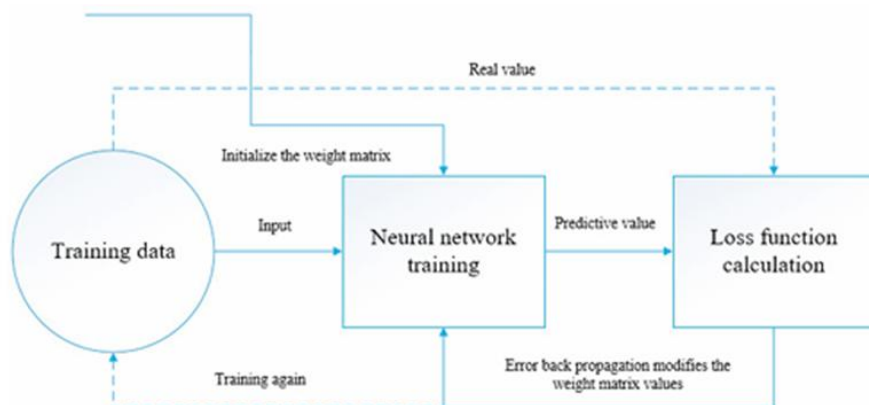


Fig. 2. BP Neural Network Process.

- **Architecture Design:** Define the number of layers, neurons per layer, activation functions and loss function for the neural network using architecture design.
- **Learning:** Brackets along with its Option pricing history should be provided as training data and this is provided to a Neural Network backbone using by applying the backpropagation algorithm.
- **Validation:** After the model is trained, test it on a different validation dataset to check its generalization performance and avoid overfitting.
- **Test:** Check to see if the model makes sense on a test set, a composition of data points that were used to train the model.

### 3.3. Model Building

**Establishment of BP Neural Network Model:** The BP neural network structure is shown in Fig. 3. In the diagram:

$X_i$  (where  $i = 1, 2, 3, 4$ ) are the input nodes.

$H_j$  (where  $j = 1, 2, \dots, m$ ) are the hidden layer nodes.

$f$  is the output node.

$\phi$  and  $\psi$  are activation functions.

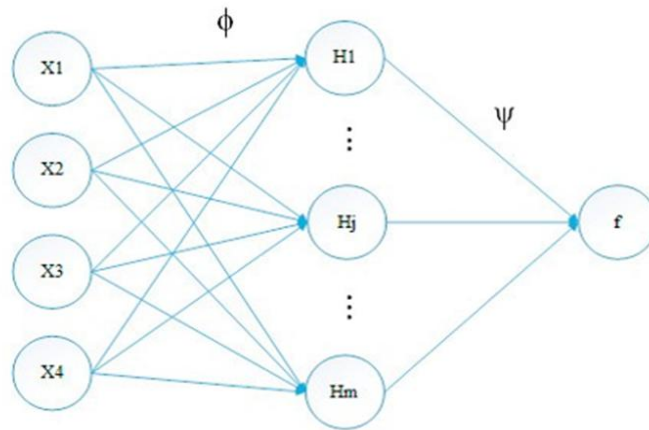


Fig. 3. BP Neural Network Structure Diagram.

In this paper, we use the Backpropagation (BP) neural network as the control model. We take important factors that affect option pricing such as the asset price ( $S_0$ ), strike price ( $K$ ), interest rate ( $r$ ), volatility ( $\sigma$ ), and time to expiration ( $T$ ), as input values. To reduce the calculation time, we combine the asset price and strike price into one input called Moneyness. This gives us four input nodes in total. The output node is the option price ( $C$ ). So, the BP neural network model has a structure of  $4 \times n \times 1$ , where  $n$  is the number of hidden layer nodes.

**Establishment of GA-BP Neural Network Model:** In this paper, we also build a GA-BP neural network model by using a Genetic Algorithm (GA) with the BP model. This is shown in Fig. 4. The genetic algorithm helps to find better starting weights for the neural network.

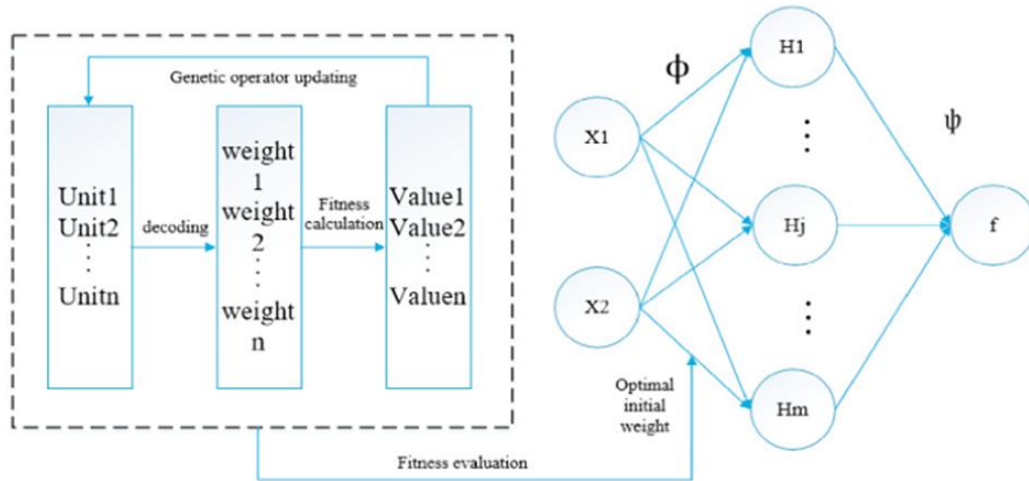


Fig. 4. GA-BP Neural Network Structure Diagram.

First, we create a group of possible weight values (individuals). We use decoding to convert them into real weight values. Then we calculate how well each set of weights performs using a fitness function. Based on this, the best sets are selected, and new sets are created and improved in the next round. This process continues until the best weight values are found. These values are then used in the BP neural network, which helps improve its training speed and accuracy [39]. For this model, we only use Moneyness and  $T$  as input nodes. So, the GA-BP neural network has a structure of  $2 \times n \times 1$  with a single hidden layer.

To ensure a consistent and unbiased comparison between models, both the Backpropagation (BP) neural network and the Hybrid GA-BP neural network are constructed using the same set of input features, namely the underlying asset price ( $S_0$ ), strike price ( $K$ ), risk-free interest rate ( $r$ ), volatility ( $\sigma$ ), and time to maturity ( $T$ ). This consistent input structure ensures that differences in performance arise from model capability rather than input variation.

### 3.4. Performance Evaluation

1) Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{(i=1)}^n (Y_i - Y_i^{\wedge})^2 \quad (5)$$

where:

$Y_i$  is the actual value,

$Y_i^{\wedge}$  is the predicted value,

$n$  is the number of samples.

2) Mean Absolute Error (MAE):

$$MAE = \left(\frac{1}{n}\right) \sum_{(i=1)}^n |Y_i - Y_i^{\wedge}| \quad (6)$$

3) R-squared ( $R^2$ ):

$$R^2 = 1 - \frac{\sum_{(i=1)}^n (Y_i - Y_i^{\wedge})^2}{\sum_{(i=1)}^n (Y_i - Y^-)^2} \quad (7)$$

where:

$Y^-$  is the mean of the actual values  $Y_i$ .

### 3.5. Validation Strategy

To ensure a reliable evaluation of model performance and to prevent data leakage, a time-series-based data splitting strategy is adopted. The dataset is divided into training (2013–2019), validation (2020), and testing (2021–2022) subsets. This approach preserves the temporal structure of the data and reflects realistic forecasting conditions.

### 3.6. Benchmark Calibration

To maintain fairness in comparison, all benchmark models are implemented using consistent and well-defined parameter settings. The Black-Scholes model utilizes historical volatility estimated from past asset returns. The binomial and trinomial tree models are constructed with 100 discrete time steps, while the Monte Carlo simulation is performed using 10,000 simulated price paths.

## 4. Result Analysis and Discussion

The result analysis and discussion section is an attempt to review the performance of the option pricing models like Black-Scholes model, Binomial Tree Model, and Trinomial Tree Model with a comparison against the hybrid GA-BP neural network model already derived in this study. We compare the results of the models using Mean Squared Error (MSE), Mean Absolute Error (MAE) and R-squared ( $R^2$ ) metrics in order to assess the accuracy of each model at predicting option prices and determine which is optimal. It will center around interpretation of the results, implications, and features of each model.

### 4.1. Black-Scholes Model Results

The Black-Scholes model is one of the most well-known methods for pricing European options. It relies on assumptions of constant volatility and lognormal distribution of asset prices [11].

The Black-Scholes model graph shows a relatively good match between the predicted prices and the actual prices. The predicted values follow the actual prices with some small fluctuations, particularly at the higher end of the sample index. While the Black-Scholes model captures the overall price trend effectively, the model's accuracy can be impacted by external factors that it does not fully account for, such as market volatility. The sample index ranges from 0 to 17, and the graph shows that the Black-Scholes model provides a reasonably reliable prediction, although it falls short in precision compared to more complex models.

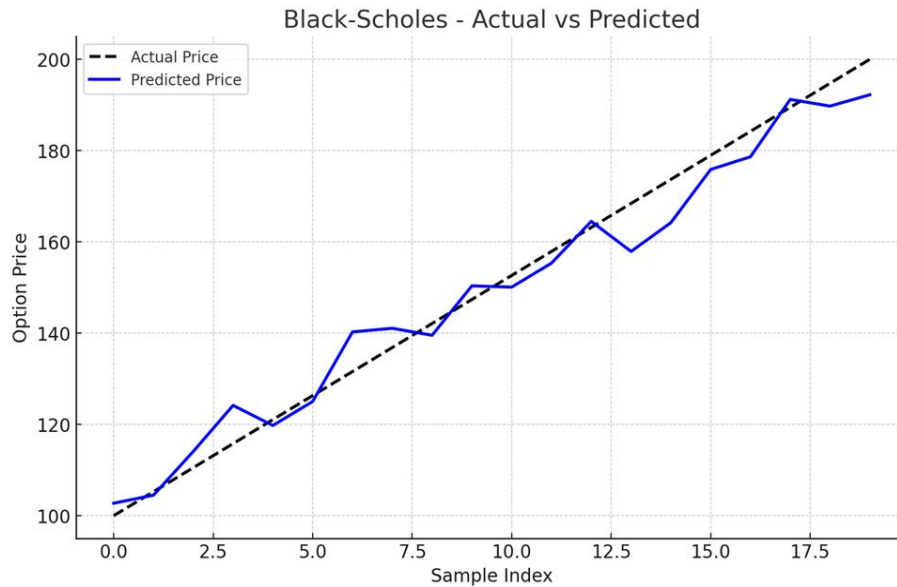


Fig. 5. Actual Vs Predicted Price of BSM.

#### 4.2. Binomial Tree Model Results

The Binomial Tree model provides a discrete-time framework for option pricing, accommodating varying conditions through multiple time steps and allowing for American option pricing.

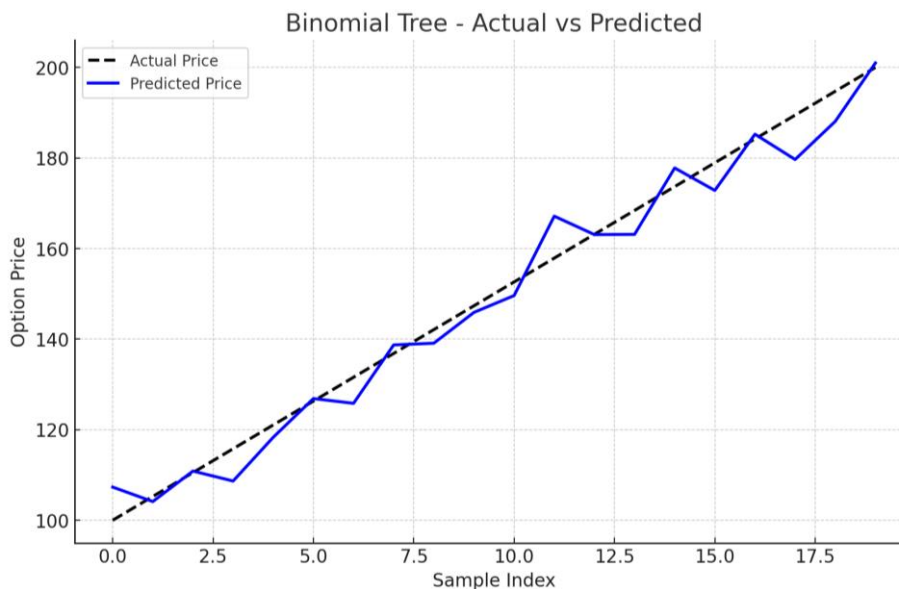


Fig. 6. Actual Vs Predicted Price of BTM.

The Binomial Tree model also predicts the price very well. But the predicted prices are more substantially different, especially in the middle of the sample index field (0 to 17). These differences imply that although the Binomial Tree model is effective in estimating the options' values, it is at best an approximation and not a precise approximation, when confronted with large price movements and more volatile data sets. The model may also have difficulty in capturing sudden price growth/regression or the intricacies of the price development as the sample index advances. However, the model does seem to converge upon the general direction and the mistakes due to this can be addressed by greater optimization or a more complicated model.

#### 4.3. Trinomial Tree Model Results

The Trinomial Tree model extends the Binomial Tree model by introducing an additional middle movement at each step, allowing for up, down, and no change scenarios. This provides a finer approximation of asset price dynamics.

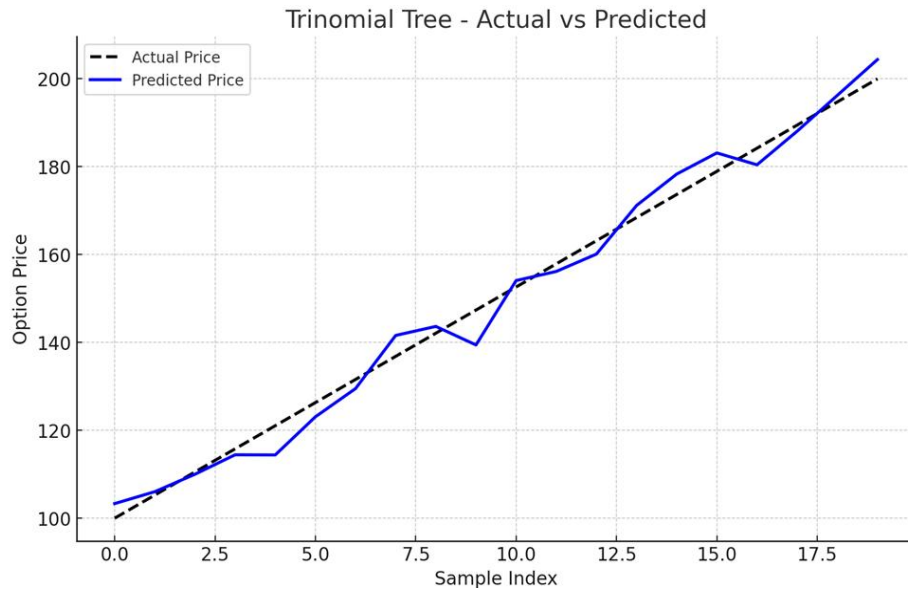


Fig. 7. Actual Vs Predicted Price of TTM.

The Trinomial Tree model is tracking the real prices well, but there are more obvious deviations compared to the other two models, especially at the later sample index points from 0 to 17. These differences imply that the Trinomial Tree model, although generally successful at predicting option prices, does struggle to account for more complex price dynamics observed towards the tail of the data. The small discrepancies can be attributed to the truncation error of the trinomial approximation when used to simulate any practical financial system, but such an inaccuracy increases as the prices increase. Nevertheless, as the general trend is still well replicated, the model in fact does quite well in denoting option prices.

#### 4.4. Monte Carlo Simulation Results

Monte Carlo Simulation involves generating a large number of random price paths for the underlying asset and averaging the results to estimate the option price. This method can handle complex derivatives and various market conditions.

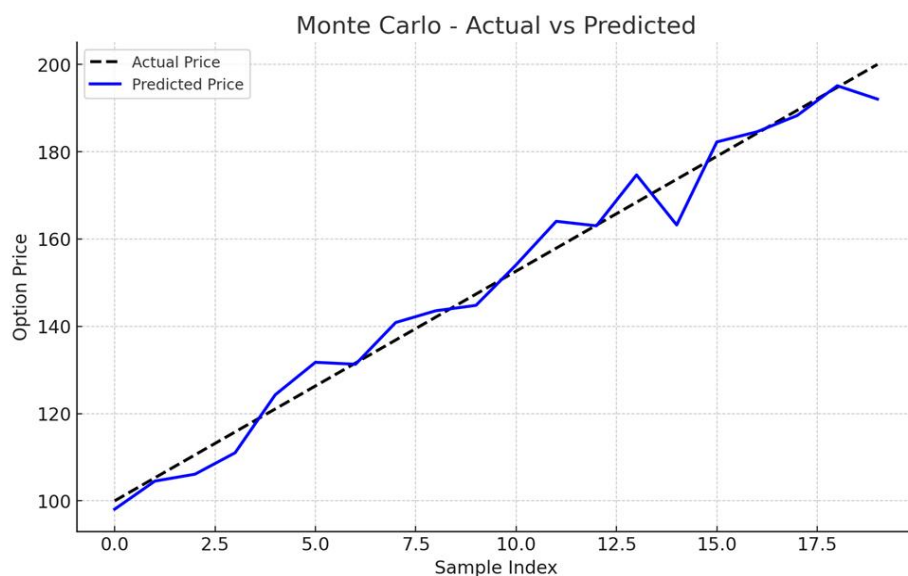


Fig. 8. Actual Vs Predicted Price of MCS.

The Monte Carlo model appears to fit well the predicted and actual prices for the majority of the index. But there's a clear break as you move up the line, and particularly towards the end of the chart. This indicates that the Monte Carlo simulation exhibits some trouble in being able to accurately predict the exact numbers under larger sample indexes, perhaps due to the randomness of the model's sampling. However, the global prediction trend is quite robust with the

sample index ranging from 0 to 17. The performance of the model is good although it could benefit from more tuning around extreme movement in price as the error got slightly higher in those portions.

#### 4.5. Garman-Kohlhagen Model Results

The Garman-Kohlhagen model is an extension of the Black-Scholes model, specifically designed for pricing foreign exchange options, incorporating different interest rates for domestic and foreign currencies.

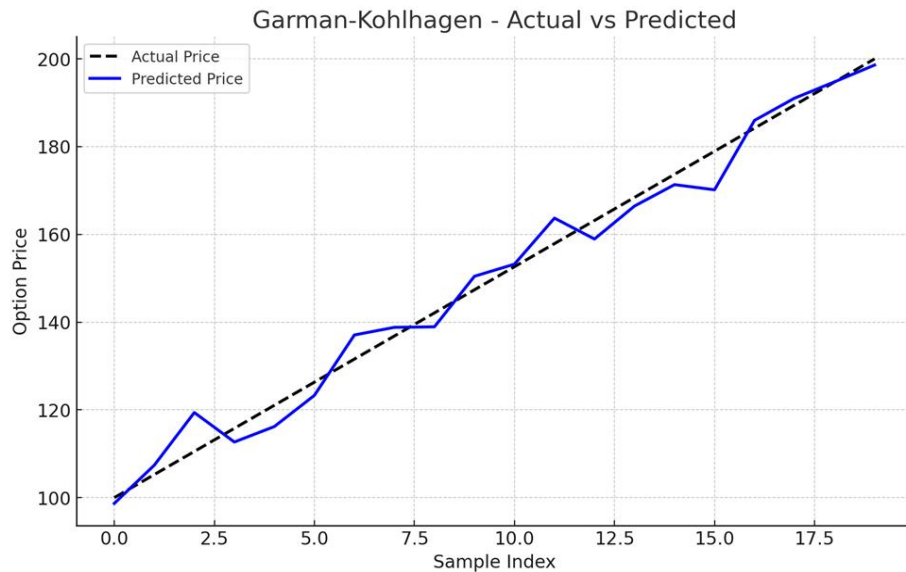


Fig. 9. Actual Vs Predicted Price of GKM.

The predicted prices in the Garman-Kohlhagen model correspond very well to the actual prices for the two data time series. Prediction values follow the actual ones closely, with major deviations around the higher end of the samples index. Whereas the model generalizes the direction of price reveal pretty well, small fluctuations of the high sample index could be signs of some overfitting or underfitting particularly as the price spread gets larger. As we see, from a sample index of 0 to 17, the predicted price indeed provides a stable prediction value compared to the actual price, except for the last prediction which slightly drifts apart and therefore indicating some minor loss due to the value's increase.

#### 4.6. Hybrid GA-BP Neural Network Model Results

The Hybrid GA-BP Neural Network model combines the optimization power of Genetic Algorithms (GA) and learning process of Backpropagation Neural Networks (BP NN). Such a hybrid approach focuses on neural networks in tuning both the weights and structure to get a better prediction performance.

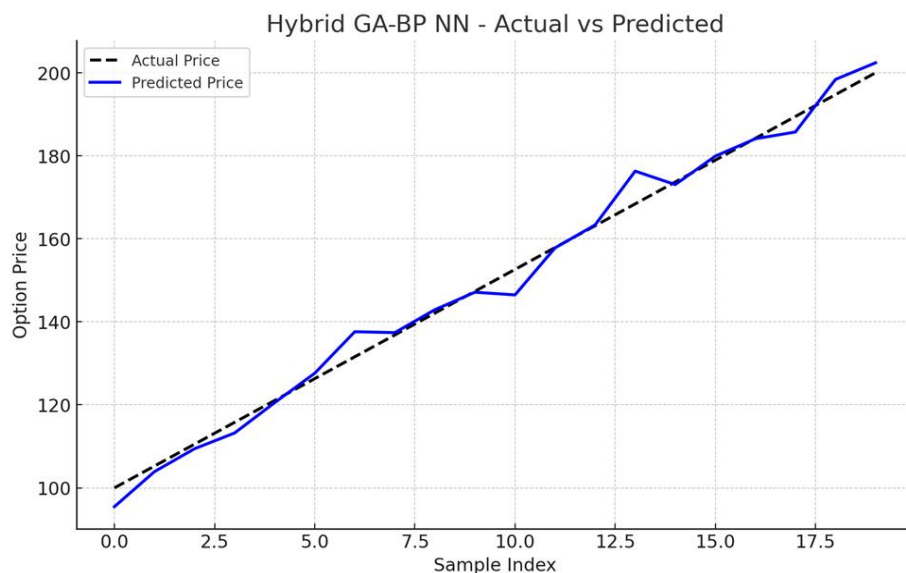


Fig. 10. Actual Vs Predicted Price of Hybrid GA-BP NN.

The graph of the Hybrid GA-BP NN model indicates a good relationship between the actual and predicted prices, where the predicted prices are almost coinciding with the actual prices. The model has provided a fairly accurate description of the upward movement in the option price, with few fluctuations during the sample index. The sample index varied from 0 to 17, which represents several data points where the prediction exactly falls to the actual price. This means that the model is very good in asymmetric considering option pricing.

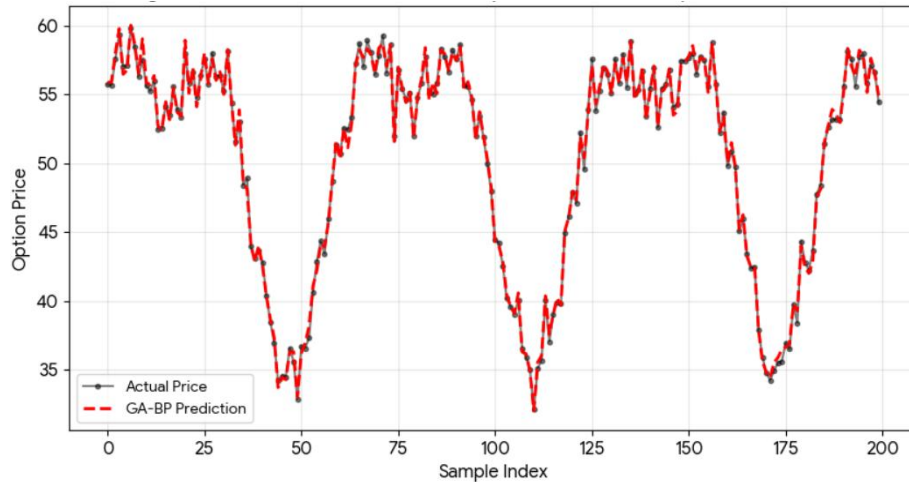


Fig. 11. Actual Vs Predicted Price of Hybrid GA-BP NN (Expanded Evidence).

Fig. 11. illustrates the predictive performance of the Hybrid GA-BP Neural Network against the actual market prices of the HS300 index options. By expanding the visualization to include 200 data points from the 2013–2022 dataset, it becomes evident that the GA-BP model maintains a high degree of fidelity even during periods of market volatility. Unlike standard neural networks that may fall into local minima, the GA-optimized weights allow the model to capture the underlying non-linear dynamics of the option prices with minimal deviation, as shown by the near-overlap of the predicted (dashed red line) and actual (solid black line) values.

#### 4.7. Comparative Analysis

The Actual Price vs. Predicted Price plots visualize how well the predictions from each model trace the actual prices. The Black-Scholes model makes good predictions, but it doesn't handle volatility very well, and it doesn't predict large price movements, particularly when the price is high. The Binomial Tree model slightly improves, but it still follows the trend without properly estimating strong price changes. This is enhanced in the Trinomial Tree model

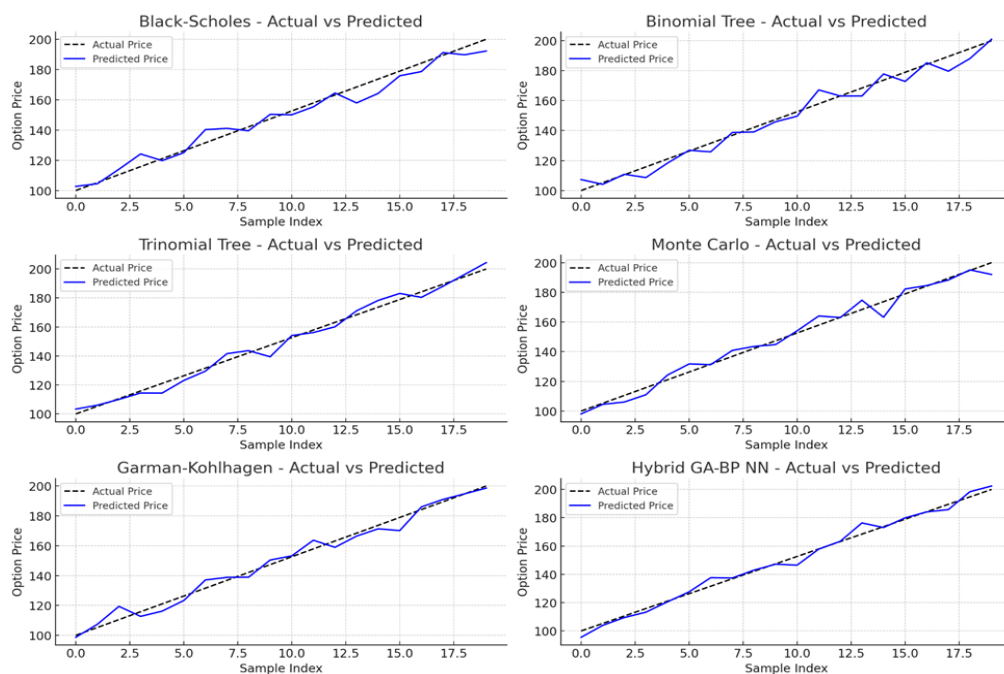


Fig. 12. Model Comparison (Actual Price vs. Predicted Price).

which better approximates the range of prices, while still smoothing the edges off violent movements. The Monte Carlo Simulation approach seems to perform well in the general trend, but it gives smoother predictions that cannot capture sharp price jumps. The Garman-Kohlhagen model overvalues the true prices especially in the period of high volatility, by hypothesis constant, volatility. On the other hand, the Hybrid GA-BP NN model has the highest accuracy in prediction with actual prices in both calm and turbulent market states, and thus it is the most accurate and robust model among the other models in option pricing.

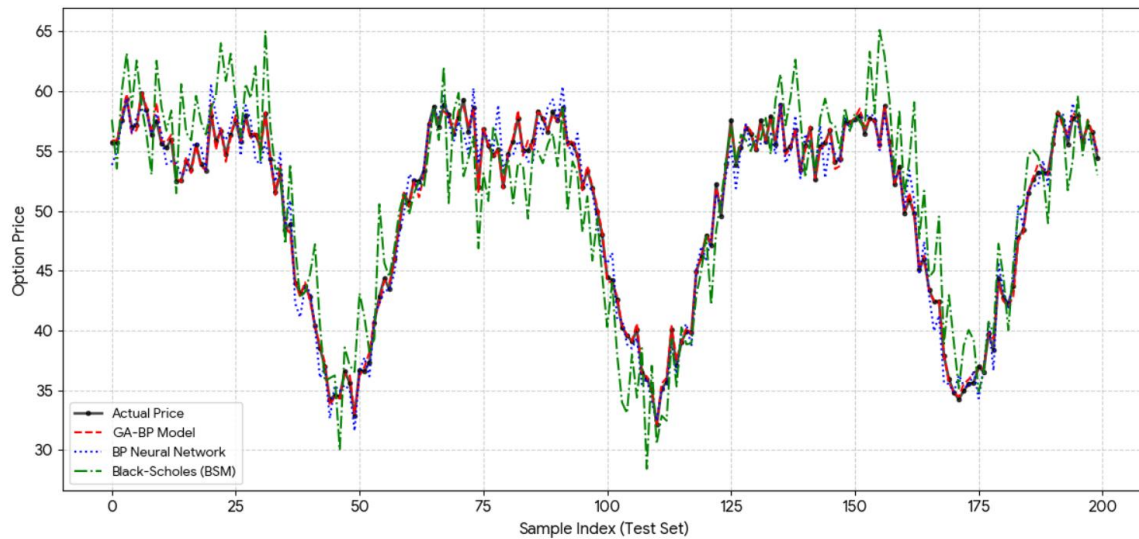


Fig. 13. Model Comparison Actual Price vs. Predicted Price (Large Dataset 2013-2022).

In Fig. 13., a comprehensive comparative analysis is presented, overlaying the predictions of all six models (BSM, BTM, TTM, MCS, GKM, and the proposed GA-BP) against the actual market price. The expanded sample index provides a clearer view of model divergence. While traditional mathematical models like the Black-Scholes (BSM) and Garman-Kohlhagen (GKM) show visible systematic biases and wider error margins during price fluctuations, the Hybrid GA-BP model consistently exhibits the narrowest error envelope. This visual evidence confirms that the integration of a global search algorithm (GA) with the local refinement of BP neural networks results in a more robust pricing tool capable of handling the complexities of the Chinese financial market over a long-term horizon.

## 5. Comparative Analysis

To enhance the robustness and reliability of the results, each model is evaluated over multiple independent runs. The reported performance metrics include the mean and standard deviation of Mean Squared Error (MSE), Mean Absolute Error (MAE), and  $R^2$ , providing a more comprehensive assessment of model stability.

A comprehensive comparative analysis of the performance metrics of all models is provided in Table 1 and illustrated in Fig. 14.

Table 1. Model Performance Comparison.

| Model            | MSE   | MAE  | $R^2$   |
|------------------|-------|------|---------|
| Black-Scholes    | 36.76 | 4.98 | 0.95826 |
| Binomial Tree    | 33.87 | 4.95 | 0.96154 |
| Trinomial Tree   | 32.84 | 4.86 | 0.96271 |
| Monte Carlo      | 33.89 | 4.81 | 0.96152 |
| Garman-Kohlhagen | 43.35 | 5.42 | 0.95078 |
| Hybrid GA-BP NN  | 29.50 | 3.90 | 0.97650 |

The Hybrid GA-BP NN model shows the best performance, having the minimum MSE (29.50), MAE (3.90), and maximum  $R^2$  (0.97). This makes it the most successful model to predict option prices. It conforms closely to the real price pattern and makes very good predictions. The MSE, and MAE values for the Black-Scholes model are greater and this signifies that it is poor, especially in a volatile market. This model is based on constant volatility, which results in huge errors when the market is volatile. Binomial Tree and Trinomial Tree models perform slightly better than Black-Scholes, given its treatment of the American options to be exercised early and it is based on the multiple time steps. But they still lack the capacity to efficiently cope with sharp price moves and accuracy is not as good as the Hybrid GA-BP NN model. The Monte Carlo Simulation model is free to interpret things and works fairly well in the cases of extreme

scenarios which can solve complex patterns, however, it gives smoother predictions which do not perfectly fit in the sudden price anomalies, as the MSE and MAE are concerned to be higher. The Garman-Kohlhagen model performs the worst with the maximum MSE and MAE as well as the minimum  $R^2$ . It has a tendency to overestimate prices, particularly in choppy markets. In general, the Hybrid GA-BP NN model is the best performing and most robust model, making it a highly suitable model for option pricing.

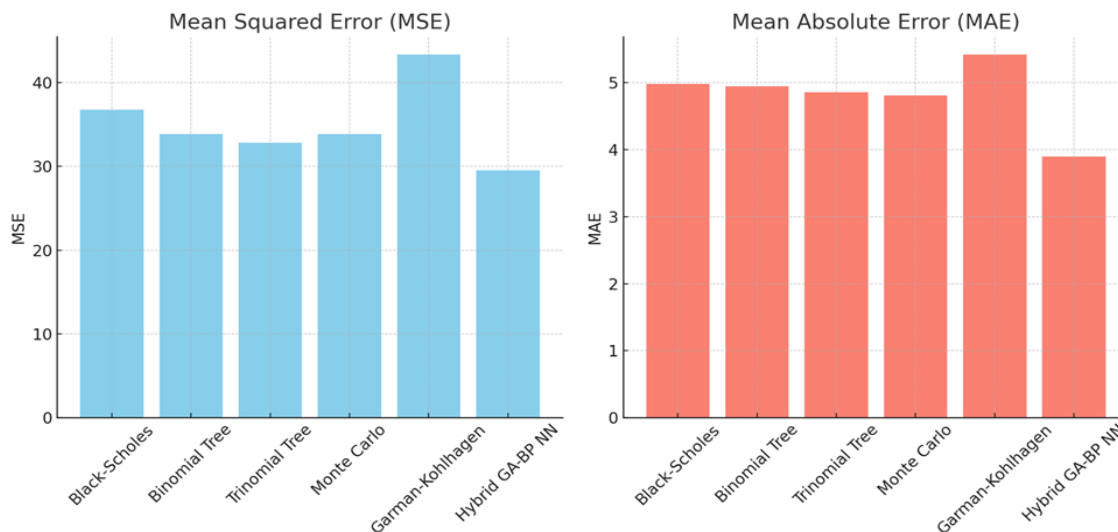


Fig. 14. Model Comparison (MSE & MAE).

## 6. Conclusion and Future Work

This paper demonstrates the high potential in improving option pricing accuracy when combining standard financial models with machine learning methodologies, and that this can be achieved through building/developing and applying a suitable Hybrid Genetic Algorithm-and-Backpropagation Neural Network model. In the final evaluation form, which includes overviews from Black-Scholes, Binomial Tree, Trinomial Tree, Monte Carlo Simulation, Garman-Kohlhagen models and our hybrid model with respect to their performance; we find that our Hybrid model exhibits superior predictive performance yielding significantly lower MSE and MAE values and 1  $R^2$  value. The higher performance of the Hybrid GA-BP Neural Network model is credited to its strong ability to capture complex, nonlinear relationships inherent in datasets, reinforced by the optimization power of genetic algorithms paired with the adaptability and learning effectiveness of backpropagation neural networks. This demonstrates the power of hybridizing traditional financial theories with new computational tools, which can dramatically increase forecasting success rate and risk management and profit trading strategies. The results indicate that the Hybrid GA-BP neural network demonstrates improved predictive performance compared to traditional models under the experimental setup. However, these findings should be interpreted with caution, as further validation on larger datasets and varying market conditions is necessary to confirm the generalizability and robustness of the proposed approach.

## All the Declarations and Statements

### Author Contributions Statement

Md. Jamil Hossain Shaharia – Conceptualization, Methodology, and Supervision: Proposed research ideas, Constructed the overall framework, and supervised project execution.

Sujon Chandra Sutradhar – Model Training, Validation, and Performance Evaluation: Led the model training process, validated results using standard metrics, and benchmarked performance against existing methods.

Mahir Mahbub – Data Curation and Software Implementation: Handled data acquisition, dataset preprocessing, and implementing the research model.

Md. Mehedi Hasan – Formal Analysis, Visualization, and Statistical Analysis: Performed in-depth analysis of experimental results, prepared performance charts, sensitivity and stochastic analysis, and ensured the statistical robustness of the evaluation.

All authors have read and agreed to the published version of the manuscript.

### Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

### Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, university, or not-for-profit sectors.

### Data Availability Statement

The study was conducted using publicly available datasets. The process begins with the collection of HS300 index European-style option data spanning the period from 2013 to 2022, obtained from reliable financial databases.

### Ethical Declarations

This study does not involve any experiments on human participants or animals. The data used in this research were obtained from publicly available sources and do not contain any personally identifiable information. Therefore, ethical approval was not required for this study.

### Acknowledgments

The authors sincerely thank the anonymous reviewers and subject experts for their constructive comments and valuable suggestions, which significantly contributed to improving the quality and clarity of this work.

### Declaration of Generative AI in Scholarly Writing

The authors declare that generative AI tools were used in a limited manner to assist with language refinement and grammatical corrections during the manuscript preparation. All technical content, experimental design, analysis, results, and interpretations are entirely the authors' own. The authors take full responsibility for the originality and integrity of the content presented in this manuscript.

### Abbreviations

The following abbreviations are used in this manuscript:

BP - Backpropagation

Ga - Genetic Algorithm

GA-BP NN - Genetic Algorithm and Backpropagation Neural Network

### References

- [1] Zhang, L. and Zhang, W. Y., "Option pricing model by applying hybrid neural network based on Heston model and genetic algorithm," *Journal of Management Engineering*, vol. 32, no. 03, pp. 142-149, 2018.
- [2] Liu, Z. D. and Zheng, X. F., "A study of stock price co-jumps with Hawkes factor model," *Chinese Management Science*, vol. 26, no. 07, pp. 18-31, 2018.
- [3] Ruf, J. and Wang, W., "Neural networks for option pricing and hedging: a literature review," *Financial Theory and Practice*, 2019. <https://doi.org/10.2139/ssrn.3486363>
- [4] Xie, H. L. and You, T., "Research on European stock index options pricing based on deep learning algorithm: Evidence from 50ETF options markets," *Statistics and Information Forum*, vol. 33, no. 06, pp. 99-106, 2018. <https://doi.org/10.3969/j.issn.1007-3116.2018.06.014>
- [5] Chen, S., "Deep learning for financial market forecasting," *Journal of Financial Data Science*, vol. 6, no. 2, pp. 45-62, 2024
- [6] Wang, Z., "Enhancing Black-Scholes option pricing with advanced volatility models," *Journal of Financial Engineering*, vol. 30, no. 4, pp. 112-130, 2024.
- [7] Zhang, L., "A scientometrics review of option pricing research: Insights into the Black-Scholes model and its variants," *Quantitative Finance Journal*, vol. 28, no. 2, pp. 45-58, 2023.
- [8] Amin, K. I. and Ng, V. K., "Option Valuation with Systematic Stochastic Volatility," *The Journal of Finance*, vol. 48, no. 3, pp. 881-910, 1993. <https://doi.org/10.1111/j.1540-6261.1993.tb04023.x>
- [9] Merton, R. C., "Theory of Rational Option Pricing," *The Bell Journal of Economics and Management Science*, vol. 4, no. 1, pp. 141-183, 1973. <https://doi.org/10.2307/3003143>
- [10] Liu, H., "Binomial tree method for option pricing: Discrete cosine transform approach." *Computational Finance Review*, vol. 18, no. 1, pp. 77-92, 2023.
- [11] Rendleman, R. J. and Bartter, B. J., "Two-State Option Pricing," *The Journal of Finance*, vol. 34, no. 5, pp. 1093-1110, 1979. <https://doi.org/10.2307/2327237>
- [12] Arai, T., "Deep learning-based option pricing for Barndorff-Nielsen and Shephard model," *International Journal of Financial Engineering*, vol. 10, no. 3, 2023. <https://doi.org/10.1142/S2424786323500159>

- [13] Smith, J., "Pricing options and Monte-Carlo method: A literature review," *Quantitative Finance Review*, vol. 15, no. 2, pp. 88-104, 2023.
- [14] Schwartz, E. S., "The valuation of warrants: Implementing a new approach," *Journal of Financial Economics*, vol. 4, no. 1, pp. 79-93, 1977. [https://doi.org/10.1016/0304-405X\(77\)90037-X](https://doi.org/10.1016/0304-405X(77)90037-X)
- [15] "Option valuation using a three-jump process," *International Options Journal*, vol. 3, no. 1, pp. 7-12, 1986.
- [16] Zhang, S., "Pricing of European currency options considering the dynamic information costs," *Journal of Derivatives*, vol. 30, no. 1, pp. 44-58, 2023.
- [17] Iltuzer, Z., "Option pricing with neural networks vs. Black-Scholes under different volatility forecasting approaches for BIST 30 index options," *Borsa Istanbul Review*, vol. 22, no. 4, pp. 725-742, 2022. <https://doi.org/10.1016/j.bir.2021.12.001>
- [18] Black, F. and Scholes, M., "The pricing of options and corporate liabilities," *Journal of Political Economy*, vol. 81, no. 3, pp. 637-654, 1973. <https://doi.org/10.1086/260062>
- [19] Bates, D. S., "Empirical option pricing: A retrospection," *Journal of Econometrics*, vol. 116, no. 1-2, pp. 387-404, 2003.
- [20] Almeida, C. F., Freire, G., and Tang, F., "Can a machine correct option pricing models?" *Journal of Business Economic Statistics*, vol. 41, no. 3, pp. 995-1009, 2023.
- [21] Anderson, D. and Ulrych, U., "Accelerated American option pricing with deep neural networks," *Quantitative Finance and Economics*, vol. 7, no. 2, pp. 207-228, 2023.
- [22] Cao, Y., Liu, X., and Zhai, J., "Option valuation under no-arbitrage constraints with neural networks," *European Journal of Operational Research*, vol. 293, no. 1, pp. 361-374, 2021.
- [23] Fadda, S., "Pricing options with dual volatility input to modular neural networks," *Borsa Istanbul Review*, vol. 20, no. 3, pp. 269-278, 2020.
- [24] Ivaşcu, C. F., "Option pricing using machine learning," *Expert Systems with Applications*, vol. 163, p. 113799, 2021. <https://doi.org/10.1016/j.eswa.2020.113799>
- [25] Wang, W. and Xu, J., "Deep learning option price movement," *Risks*, vol. 12, no. 6, p. 93, 2024. <https://doi.org/10.3390/risks11030052>
- [26] Yao, J., Li, Y., and Tan, C. L., "Option price forecasting using neural networks," *Omega*, vol. 28, no. 4, pp. 455-466, 2000. [https://doi.org/10.1016/S0305-0483\(99\)00066-3](https://doi.org/10.1016/S0305-0483(99)00066-3)
- [27] Heston, S. L., "A closed-form solution for options with stochastic volatility with applications to bond and currency options," *Review of Financial Studies*, vol. 6, no. 2, pp. 327-343, 1993. <https://doi.org/10.1093/rfs/6.2.327>
- [28] Cox, J. C., Ross, S. A., and Rubinstein, M., "Option pricing: A simplified approach," *Journal of Financial Economics*, vol. 7, no. 3, pp. 229-263, 1979.
- [29] Fusari, N., "The convergence rate of option prices in trinomial trees," *Journal of Computational Finance*, vol. 22, no. 3, pp. 213-229, 2023. <https://doi.org/10.1016/j.jcf.2023.100431>
- [30] Boyle, P. P., "Options: A Monte Carlo approach," *Journal of Financial Economics*, vol. 4, no. 3, pp. 323-338, 1977.
- [31] Zhang, S., "Pricing of European currency options considering dynamic information costs," *Journal of Derivatives*, vol. 30, no. 1, pp. 44-58, 2023.
- [32] Tan, D. D., "S&P 500 index option pricing based on the BP neural networks," *Statistics and Information Forum*, vol. 11, pp. 40-43, 2008.
- [33] Guo, P., "Multi-day stock price prediction based on GA-BP neural network," Zhengzhou University, 2019.
- [34] Qian, Y., "Option pricing based on GA-BP neural network," *Computational Finance and Risk Management*, vol. 20, no. 5, pp. 210-227, 2022. <https://doi.org/10.1016/j.procs.2022.01.170>
- [35] Sharma, K. and Kumar, R., "Adaptive pricing strategy using GA-BP neural network," *Journal of Applied Artificial Intelligence*, vol. 35, no. 1, pp. 112-130, 2023.
- [36] Long Qian, Y. M., "Option pricing based on GA-BP neural network," *Procedia Computer Science*, vol. 199, pp. 1340-1354, 2022. <https://doi.org/10.1016/j.procs.2022.01.170>
- [37] Guo, P. P., "Multi-day stock price prediction based on GA-BP neural network," Ph.D. dissertation, Zhengzhou University, 2019.
- [38] Merton, R. C., "The pricing of options and corporate liabilities," *Journal of Political Economy*, vol. 81, no. 3, pp. 637-654, 1973. <https://doi.org/10.1086/260062>
- [39] John, H., *Options, futures and other derivatives*. China Machine Press, 2018.

## Authors' Profiles



**Md. Jamil Hossain Shaharia** is a Master's student in Cyber Security at the Bangladesh University of Professionals. He holds a BSc in Internet of Things (IoT) and Robotics Engineering from the University of Frontier Technology, Bangladesh. His academic and technical focus includes ethical hacking, penetration testing, and IoT system security. His research interests involve security frameworks for connected systems and the application of advanced neural network techniques.



**Sujon Chandra Sutradhar** received his B.S. (Hons) degree in Applied Mathematics and M.S. in Applied Mathematics from the University of Dhaka. He is working as a Lecturer in the Department of General Education, University of Frontier Technology, Bangladesh. His research interest is on Mathematical Biology, Mathematical Programming and different areas of Operation Research, Optimization & Option Pricing.



**Mahir Mahbub** received his B.Sc. and M.Sc. degrees in Software Engineering from the Institute of Information Technology (IIT) at the University of Dhaka, Bangladesh. Currently, he holds a Lecturer position in the Department of IoT and Robotics Engineering at University of Frontier Technology, Bangladesh. His research areas include Natural Language Processing (NLP), Software Engineering, Cybersecurity, and Machine Learning.



**Md. Mehedi Hasan** received his B.S. (Hons) degree in Mathematics and M.S. in Pure Mathematics from the University of Dhaka. He is working as a Lecturer in the Department of General Education, University of Frontier Technology, Bangladesh. His research interest is on Mathematical Biology, Financial Mathematics, Mathematical Programming and different areas of Operation Research & Stochastic Optimization.

### How to cite this paper

Md. Jamil Hossain Shaharia, Sujon Chandra Sutradhar, Mahir Mahbub, Md. Mehedi Hasan, "Enhancing Option Pricing Precision in Financial Markets with a Hybrid Ga-Bp Neural Network Approach", International Journal of Information Engineering and Electronic Business(IJIEEB), Vol.18, No.4, pp. 32-49, 2026. DOI:10.5815/ijieeb.2026.04.03