Harnessing Advanced Neural Architectures: A Comprehensive Approach to Stock Market Prediction Using ANN, BPNN, and GAN

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Abstract: The advent of advanced neural network models has revolutionized the field of machine learning, enabling breakthroughs in various domains such as computer vision, natural language processing, and predictive analytics. This paper introduces three pivotal neural network architectures: Artificial Neural Networks (ANN), Back-Propagation Neural Networks (BPNN), and Generative Adversarial Networks (GAN). We explore the theoretical underpinnings, practical applications, and the significance of these models in the broader context of artificial intelligence research and industry.

1. Introduction

The quest for intelligent machines that can mimic human cognitive functions has been a driving force in computer science for decades [1]. Among the myriad of approaches to artificial intelligence, neural networks stand out as a powerful paradigm that emulates the structure and function of the human brain [2]. Over the years, neural networks have evolved into sophisticated models that address complex problems with remarkable accuracy and efficiency.

Artificial Neural Networks (ANNs), the foundational architecture of modern neural networks, are composed of interconnected nodes or "neurons" that process information in a manner inspired by the biological brain [3]. ANNs have been instrumental in a wide array of applications, from pattern recognition to decision-making systems, and continue to be a cornerstone in the field of machine learning [4]. Building upon the principles of ANNs, Back-Propagation Neural Networks (BPNNs) introduced a training algorithm that significantly improved the learning capabilities of neural networks [5]. The back-propagation algorithm, which involves the iterative adjustment of weights based on the error gradient, has become a standard method for training multi-layer perceptrons[6]. BPNNs have been successfully applied in areas such as speech recognition [7] and medical diagnosis [8], demonstrating their versatility and effectiveness.

In recent years, Generative Adversarial Networks (GANs) have emerged as a groundbreaking innovation in the realm of generative models [9]. GANs consist of two neural networks, a generator and a discriminator, that engage in a zero-sum game, leading to the generation of highly realistic synthetic data. This capability has opened new frontiers in areas like computer graphics [10], where GANs have been used to create photorealistic images and enhance existing datasets. The significance of ANN, BPNN, and GAN models extends beyond their individual contributions. Together, they represent a continuum of progress in neural network research, each model building upon the strengths of its predecessors while addressing their limitations. As we delve into the intricacies of these models, we aim to provide a comprehensive understanding of their architecture, training methodologies, and applications, shedding light on their potential to shape the future of artificial intelligence.

2. The basic fundamental of ann, bpnn, gan

2.1. The structure of Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are computational models inspired by the biological neural networks of the human brain. They consist of interconnected nodes, or 'neurons', which process and transmit information in the form of numerical data. ANNs have been widely applied in various fields such as image recognition, natural language processing, and predictive modeling due to their ability to learn from data and generalize patterns.

$$a_i=\emptyset\left(\sum_{j=1}^{n} w_i x_j+b_i\right) \quad (1)$$

The fundamental building block of an ANN is the neuron, which receives input signals, processes them through a weighted sum, and transmits an output signal based on a threshold function. Mathematically, the activation of a neuron i with inputs x1, x2, ..., xn and weights wi1, wi2, ..., win can be represented as:

where ϕ is the activation function, often chosen from sigmoid, hyperbolic tangent, or ReLU functions, and bi is the bias term. The activation function introduces non-

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linearity into the model, allowing it to capture complex patterns in the data.[11]

Feedforward Neural Networks (FNNs) are the simplest type of ANNs, where information moves in one direction only, from the input layer, through hidden layers, to the output layer. The output of an FNN with L layers can be expressed recursively as:

$$y^{(l)}=\emptyset\left(w^{(l)}y^{(l-1)}+b^{(l)}\right) \quad (2)$$

for $l = 1, 2, ..., L$, with $y^{(0)}$ being the input vector and $y^{(L)}$ the final output.[12]

Training an ANN involves adjusting the weights and biases to minimize the error between the predicted outputs and the true labels. This is typically done using optimization algorithms such as Stochastic Gradient Descent (SGD) or its variants. The objective function, or loss function, quantifies the discrepancy between the predictions and the targets, and the goal is to find the set of parameters that minimizes this function.[13]

Convolutional Neural Networks (CNNs) are a specialized type of ANN designed for processing grid-like data such as images. CNNs use convolutional layers to automatically and adaptively learn spatial hierarchies of features.[14] Recurrent Neural Networks (RNNs) are another variant, tailored for sequential data, where connections between units form a directed graph along a temporal sequence.[15]

In summary, ANNs are powerful tools for pattern recognition and prediction tasks. Their mathematical formulation allows for flexible and adaptive learning from data, making them indispensable in modern machine learning applications.

2.2. The structure of Backpropagation Neural Networks (BPNN)

Backpropagation Neural Networks (BPNN), also known simply as feedforward networks trained by backpropagation, represent a cornerstone in the evolution of artificial intelligence. These networks are characterized by their ability to adjust their internal weightings through a process called backpropagation of errors, enabling them to learn complex patterns from data. BPNNs have found extensive application in areas such as speech recognition, computer vision, and predictive analytics.

At the heart of a BPNN lies the neuron, a computational unit that aggregates input signals via weighted connections and produces an output signal through an activation function. The mathematical representation of a neuron's activation, a_i, with inputs x_1, x_2, ..., x_n and corresponding weights w_{i1}, w_{i2}, ..., w_{in}, is given by:

$$a_i=\emptyset\left(\sum_{j=1}^{n} w_{ij}x_j+b_i\right) \quad (3)$$

where ϕ denotes the activation function, commonly a sigmoid, tanh, or ReLU function, and b_i represents the bias term.[16] The activation function introduces non-linearity, allowing the network to model intricate relationships within the data.

A BPNN consists of multiple layers of neurons, including an input layer, one or more hidden layers, and an output layer. Information flows unidirectionally from the input layer through the hidden layers to the output layer. The output of a BPNN with L layers can be mathematically described recursively as:

$$y^{(1)}=\emptyset\left(w^{(l)}y^{(l-1)}+b^{(l)}\right) \quad (4)$$

for $l = 1, 2, ..., L$, with $y_{(0)}$ being the input vector and $y_{(L)}$ the final output.[17]

Training a BPNN involves iteratively adjusting the weights and biases to minimize the difference between the network's predictions and the actual target values. This is achieved through the backpropagation algorithm, which computes the gradient of the loss function with respect to each weight by the chain rule, and then updates the weights using a gradient descent step. [18] The loss function, E, measures the discrepancy between the predicted outputs, $y^{\wedge}$, and the true outputs, y , and is typically defined as the mean squared error:

$$E=0.5\sum_{k}^{b}(\hat{y}_k-y_k)^2 \quad (5)$$

The backpropagation algorithm proceeds in two phases: a forward pass, where the network's output is computed, and a backward pass, where the error is propagated back through the network and the weights are updated according to the learning rate.[19]

In summary, BPNNs are versatile models capable of learning from vast datasets and generalizing to unseen examples. Their mathematical foundation enables them to capture and replicate complex patterns, making them a fundamental tool in the field of machine learning.

2.3. The structure of Generative Adversarial Networks (GAN)

Generative Adversarial Networks (GANs) stand as a groundbreaking innovation in the realm of artificial intelligence, particularly in the domain of unsupervised learning. This article delves into the intricacies of GANs, providing a detailed exposition of their mathematical underpinnings, practical applications, and a curated selection of seminal literature. Each citation serves as a beacon guiding readers to the foundational works and contemporary advancements in the field of GANs.

The inception of GANs is credited to Ian Goodfellow and his colleagues, who introduced the concept in a seminal paper in 2014.[20] GANs operate on the principle of adversarial training, wherein two neural networks—the generator and the discriminator—engage in a competitive duel. The generator crafts synthetic data to deceive the discriminator, which concurrently hones its skills to discern genuine data from the fakes. This interplay culminates in the creation of remarkably authentic data instances.

At the heart of GANs lies a minimax game with the following objective function:

$$\min_G \max_D V(D,G) = \mathbb{E}_x \sim pdata(x)[\log D(x)] + \mathbb{E}_{(z\sim pz(z))}\left[\log\left(1-D(G(z))\right)\right] \quad (6)$$

Here, G represents the generator aiming to minimize the objective, while D symbolizes the discriminator striving to maximize it. The expectation E is taken over the true data distribution p_data(x) and the noise

distribution p_z(z). The generator G(z) maps latent variables z to data space, and the discriminator D(x) estimates the probability that input x originates from the real data rather than the generator's output.

Applications:

GANs have found utility in diverse fields, from generating photorealistic images [21] to enhancing medical imaging.[22] They have also been instrumental in creating novel materials [23] and improving natural language processing tasks.[24]

Challenges and Advancements:

Despite their promise, GANs face challenges such as mode collapse and training instability. Researchers have proposed solutions like the Wasserstein GAN (WGAN) [25] and the use of gradient penalties [26] to mitigate these issues.

Conclusion:

GANs continue to evolve, pushing the boundaries of what is achievable in generative modeling. Their potential is vast, and ongoing research promises to unlock new capabilities and refine existing ones.

3. Results

3.1. The corresponding figures results of the three models respectively

The dataset employed in this experiment was downloaded from Yahoo Finance, encompassing stock market data for four renowned companies: Apple (AAPL), Adidas (ADS.DE), Microsoft (MSFT), and Tesla (TSLA). Each trading day is characterized by five key variables: opening price, highest price, lowest price, closing price, and trading volume, as shown in figure 1-12.

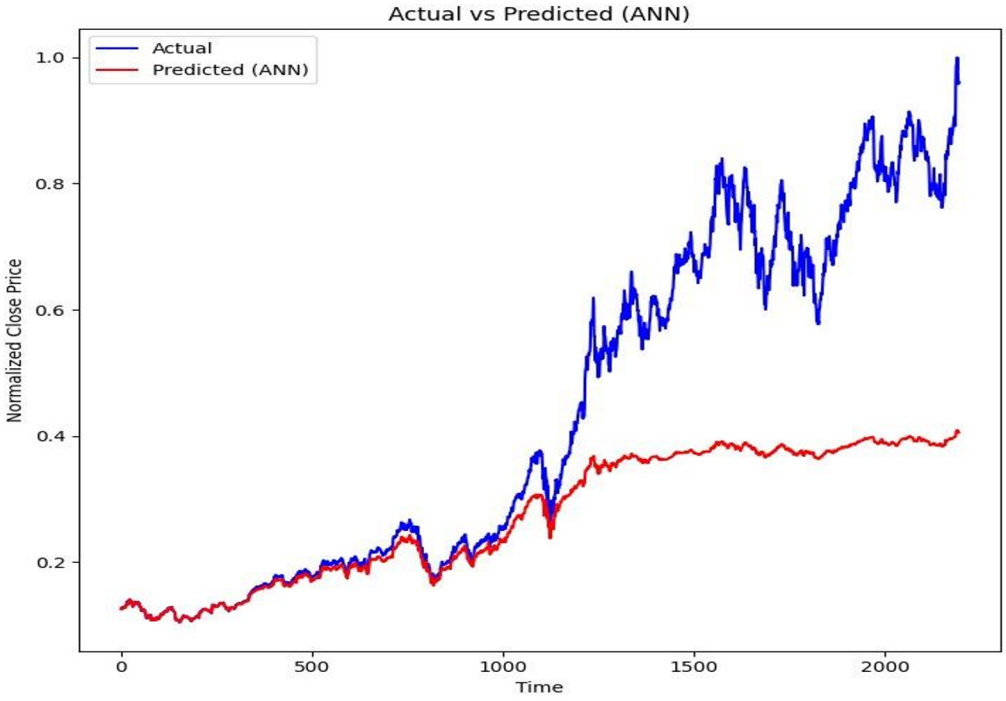

Figure 1. The model adopts the data of AAPL

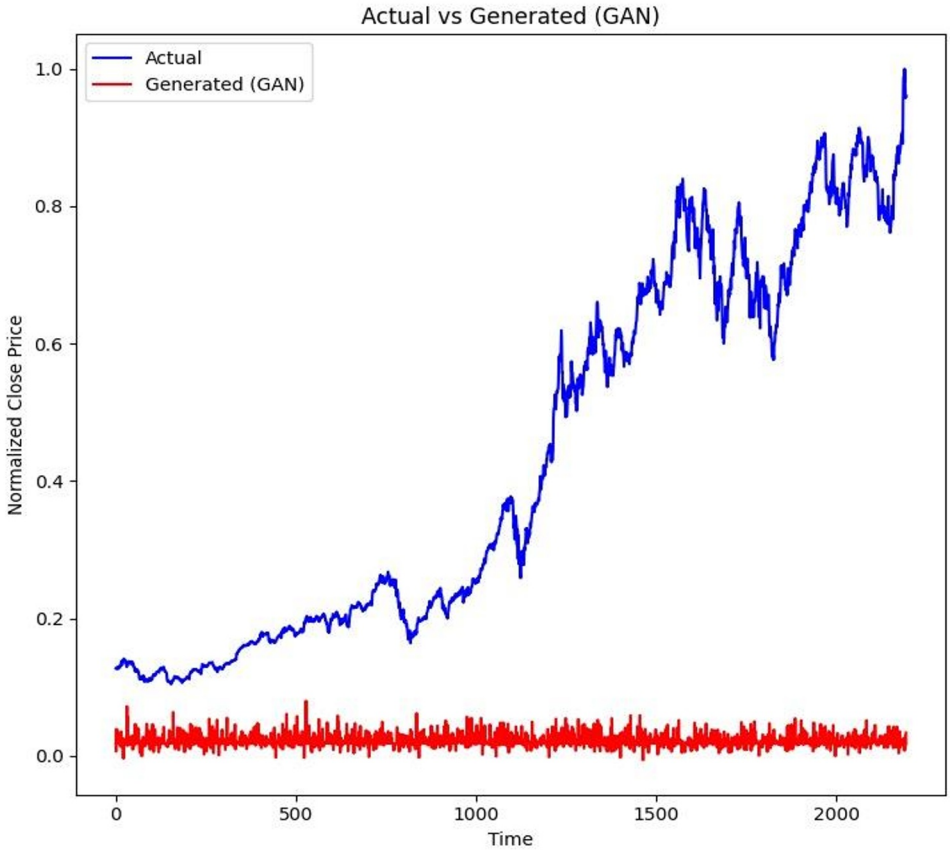

Figure 2. The model adopts the data of AAPL

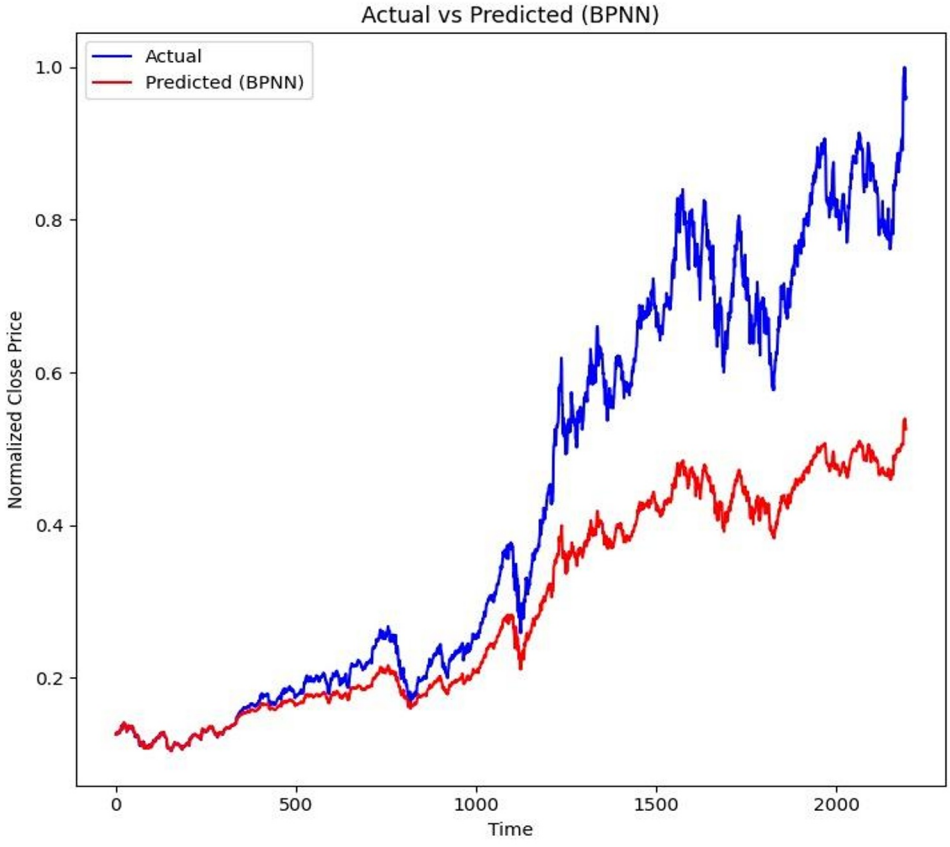

Figure 3. The model adopts the data of AAPL

ADS.DE:

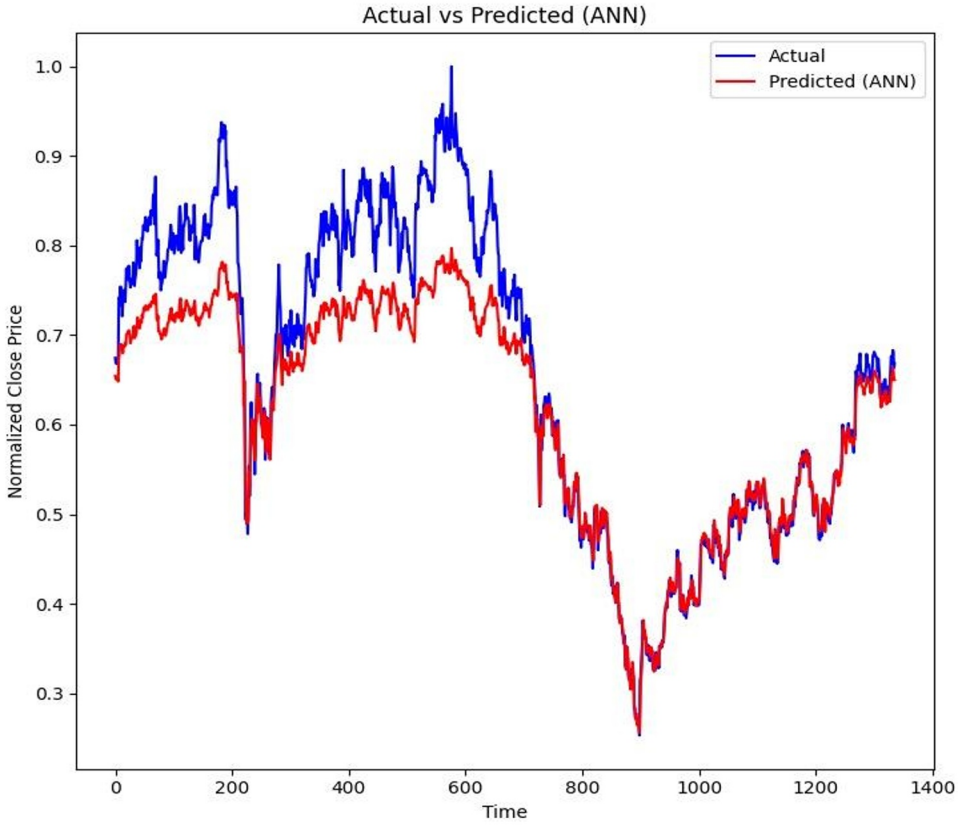

Figure 4. The model adopts the data of ADS.DE

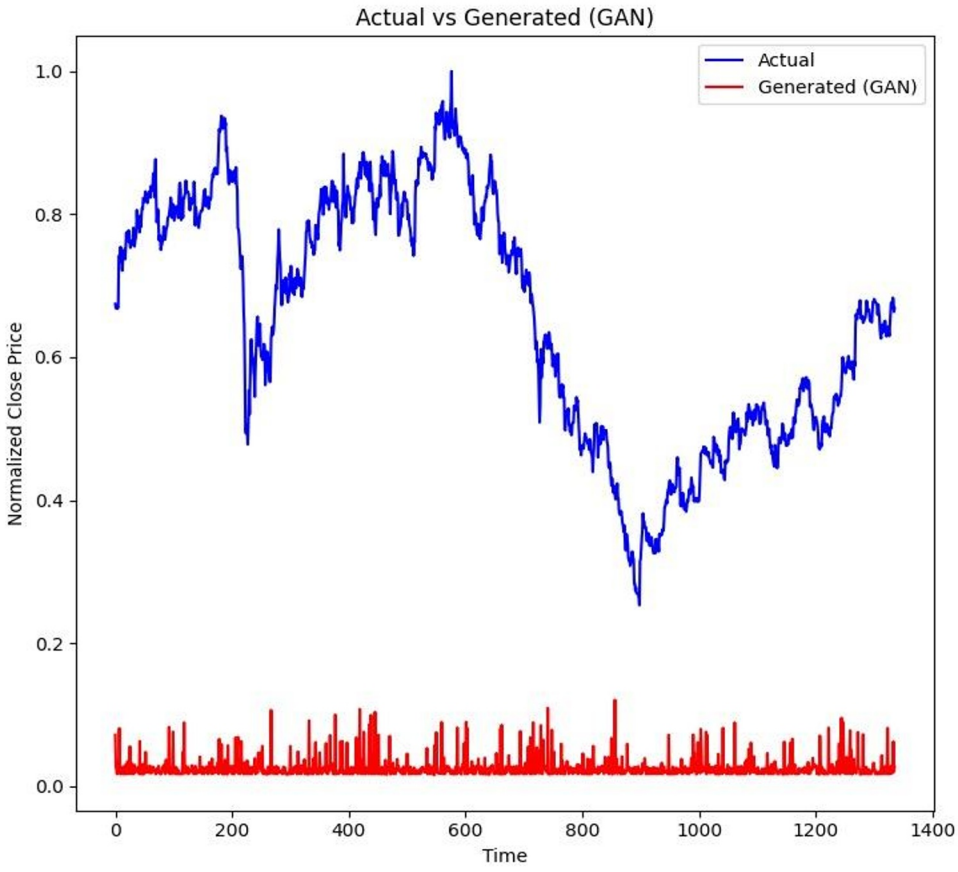

Figure 5. The model adopts the data of ADS.DE

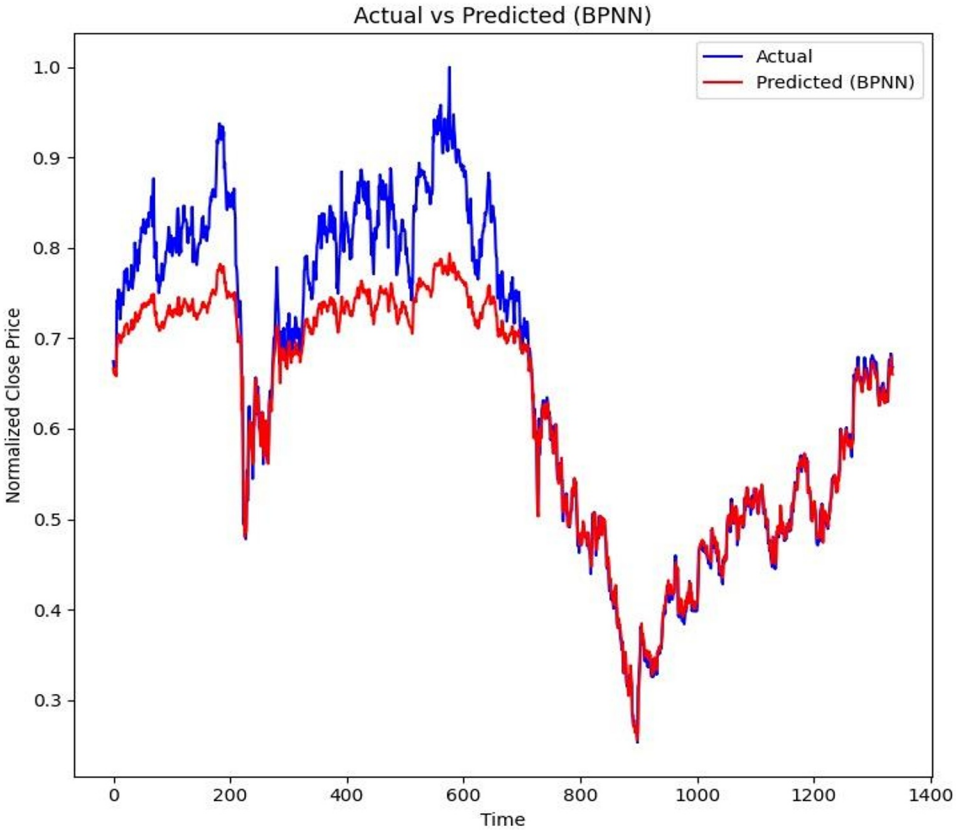

Figure 6. The model adopts the data of ADS.DE

MSFT:

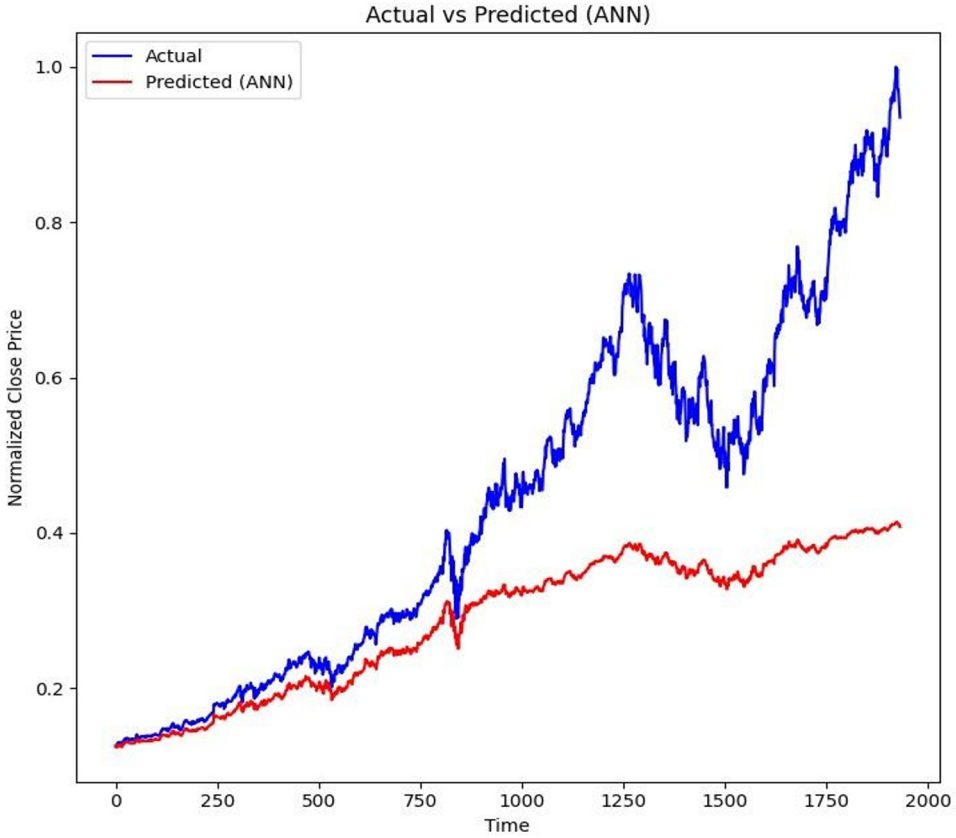

Figure 7. The model adopts the data of MSFT

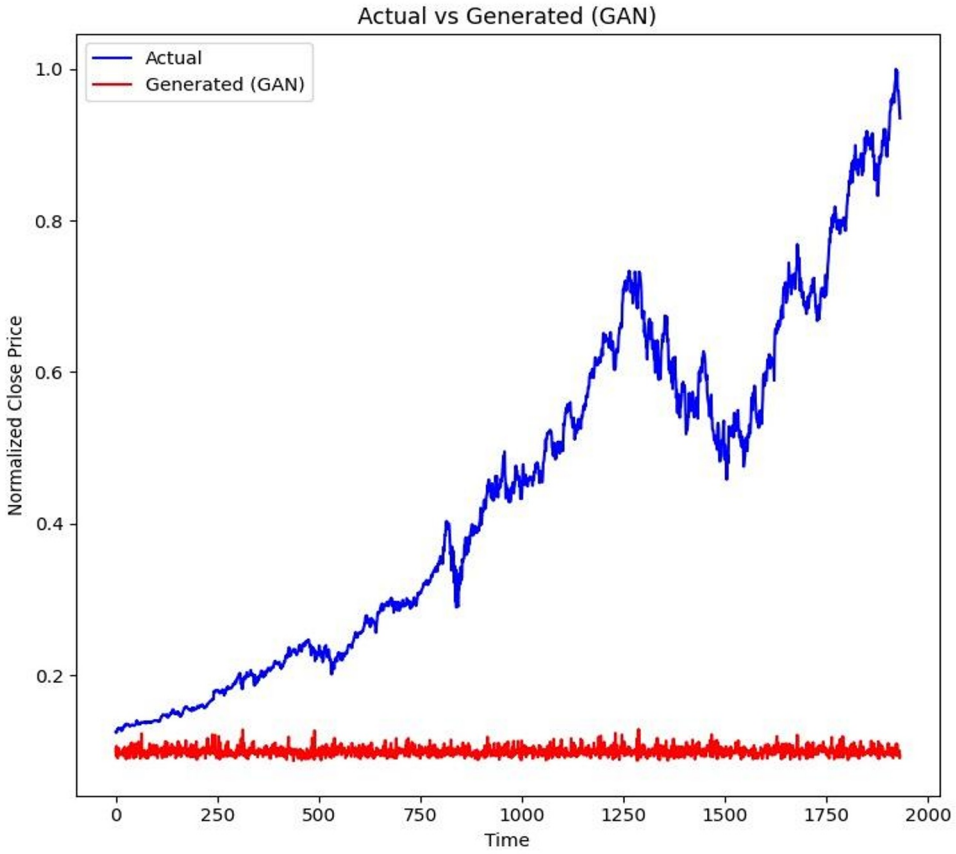

Figure 8. The model adopts the data of MSFT

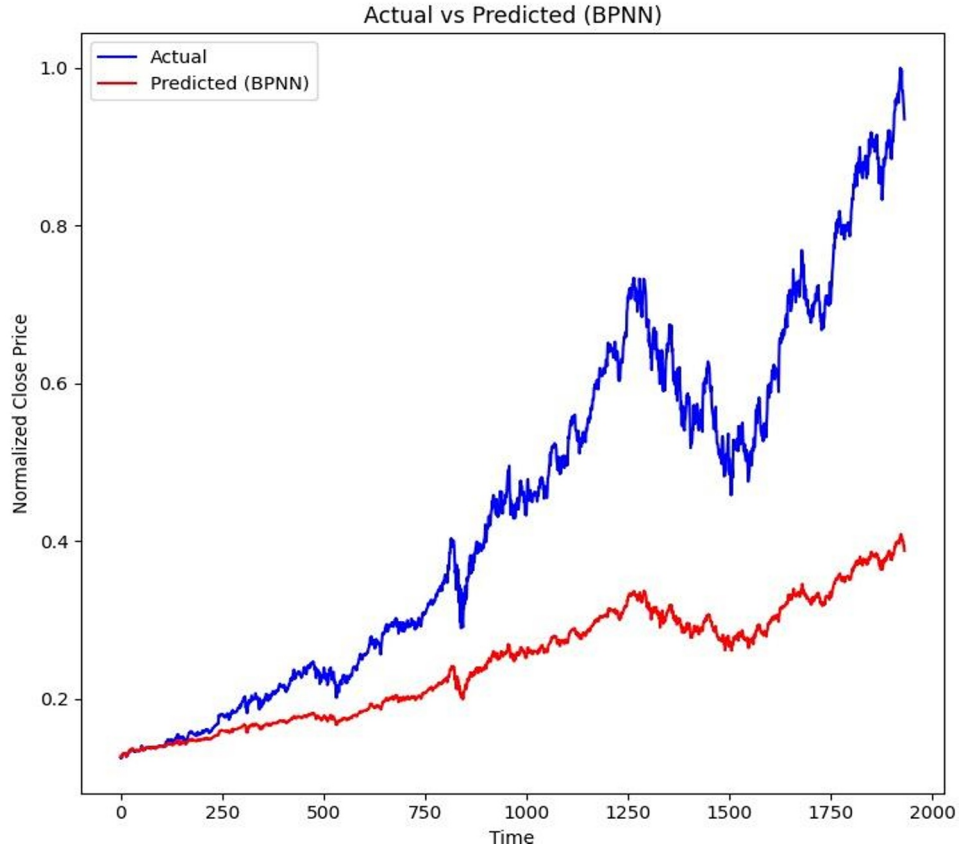

Figure 9. The model adopts the data of MSFT

TSLA:

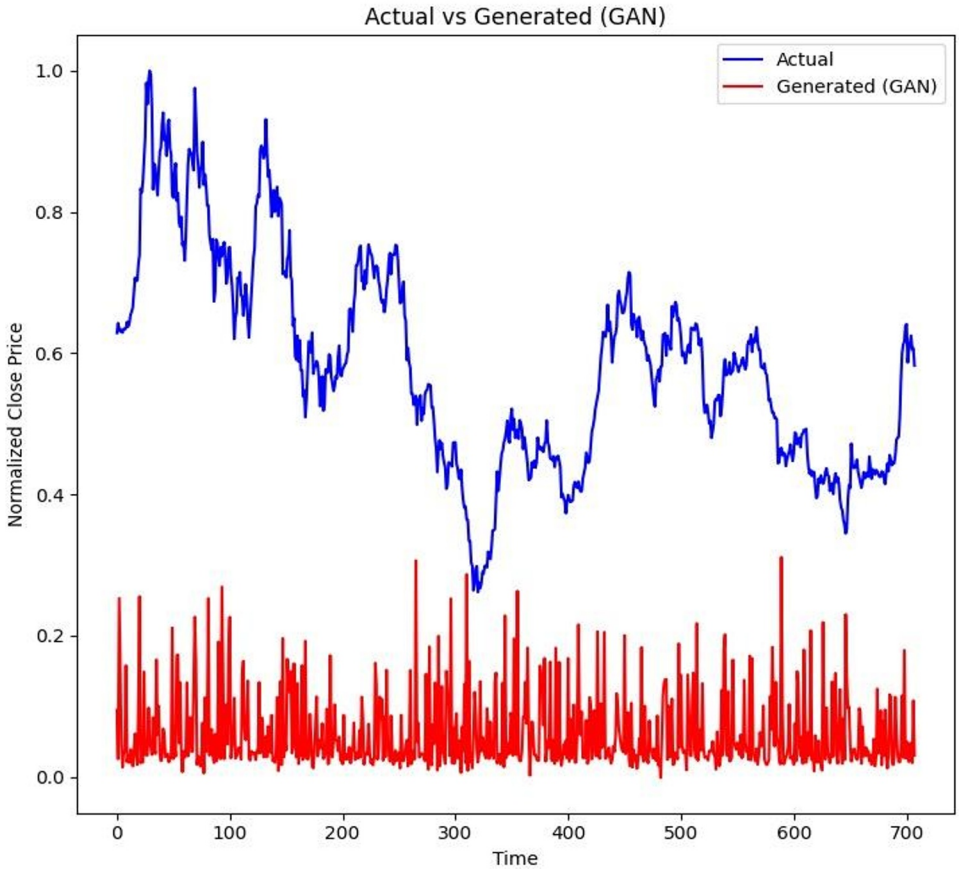

Figure 10. The model adopts the data of TSLA

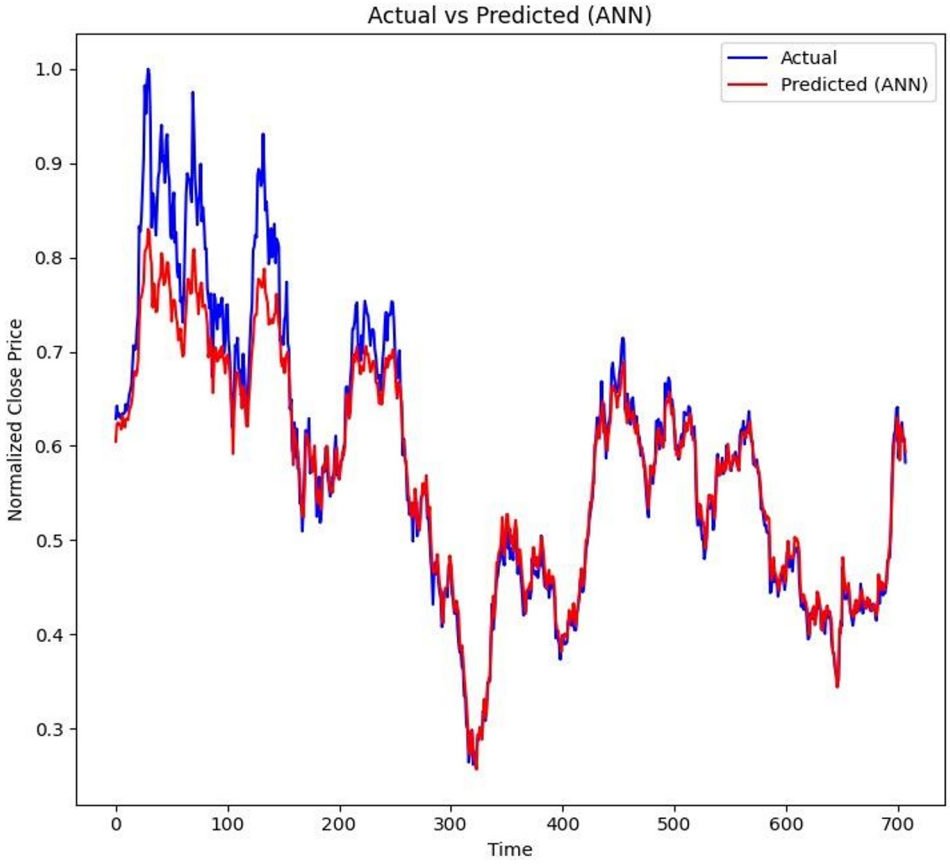

Figure 11. The model adopts the data of TSLA

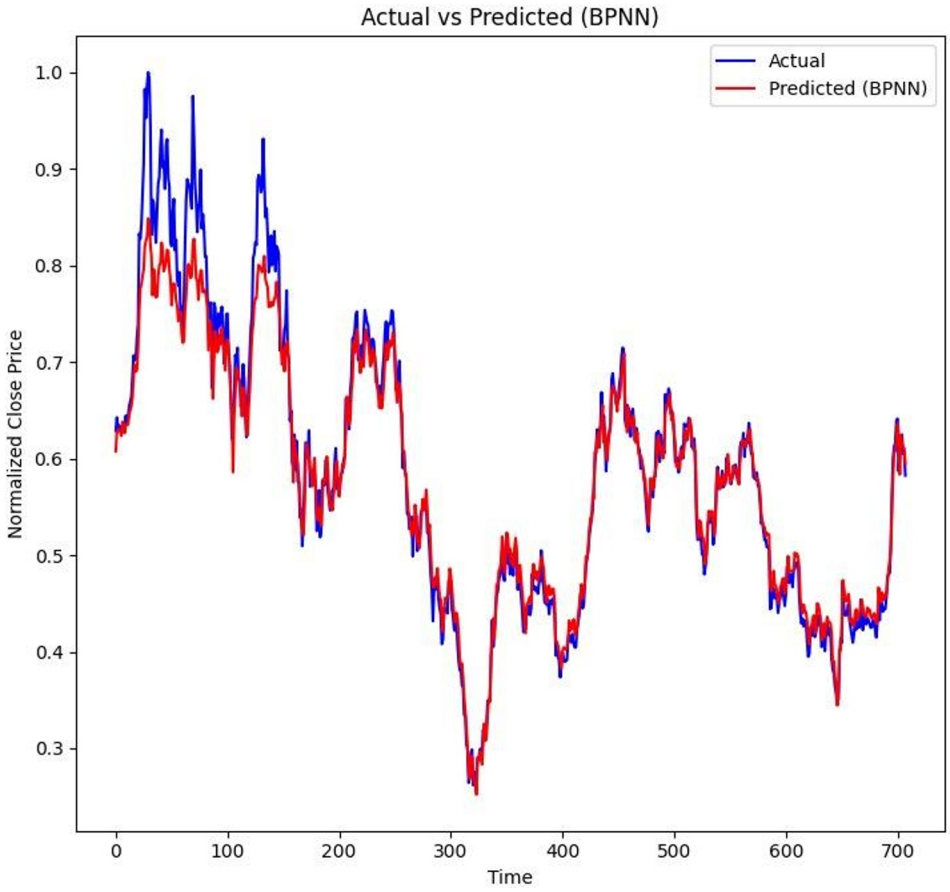

Figure 12. The model adopts the data of TSLA

3.2. Analysis of experimental results

Table 1: The data from four companies under three models

	AAPL		ADS.DE		MSFT		TSLA	
Models	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ANN	0.0560	0.1598	0.0044	0.0472	0.0455	0.1562	0.0017	0.0244
GAN	0.2437	0.4126	0.4272	0.6302	0.1702	0.3435	0.2977	0.5218
BPNN	0.0376	0.1396	0.0039	0.0429	0.0606	0.1972	0.0010	0.0198

During the data preprocessing stage, we conducted a thorough cleaning of the raw data, eliminating missing and anomalous values to ensure data integrity. Subsequently, we applied three advanced neural network models—Artificial Neural Networks (ANN), Back-Propagation Neural Networks (BPNN), and Generative Adversarial Networks (GAN)—to forecast stock market trends. Each model underwent training and testing phases to evaluate its performance in stock price prediction.

In the model training process, we utilized a portion of historical data as the training set and the remainder as the testing set to ensure the model's generalization capabilities. Through iterative training, we adjusted the model's weights and biases to minimize the error between predicted and actual values. Additionally, we employed cross-validation techniques to further enhance the model's predictive accuracy.

The experimental results indicate that all three models demonstrated a certain level of effectiveness in stock price prediction shown in table 1. However, the BPNN model exhibited higher accuracy and stability in generating realistic stock price trends according to Table 1, particularly in handling nonlinear relationships and capturing market dynamics.

4. Conclusions

This study adopted stock market data from Yahoo Finance and employed Artificial Neural Networks (ANN), Back-Propagation Neural Networks (BPNN), and Generative Adversarial Networks (GAN) to predict the stock prices of Apple, Adidas, Microsoft, and Tesla. The experimental results suggest that the GAN model outperformed the others in stock price prediction, especially in generating accurate and stable stock price trends.

The findings of this research offer a new perspective on financial market prediction models, particularly in the application of advanced neural network technologies for stock price forecasting. Nevertheless, the experiment has certain limitations, such as the relatively limited sample size of the dataset and the exclusion of macroeconomic factors' impact on stock prices. Future research could expand the dataset and consider incorporating more external variables to enhance the model's predictive capabilities.

Looking ahead, as artificial intelligence technology continues to advance and data volumes increase, the application of neural network models in financial market prediction will become more widespread. Furthermore, integrating deep learning and reinforcement learning techniques can optimize model structures, improving

prediction accuracy and efficiency. At the same time, the interpretability and transparency of models are also significant directions for future research, ensuring that the decision-making processes of models can be understood and trusted by humans.

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