EXPLORING DEEP LEARNING AND GAN MODELS FOR LEVERAGING STOCK PRICES PREDICTION: A NOVEL ADVERSARIAL FRAMEWORK FOR FINANCIAL TIME SERIES FORECASTING

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Abstract
Predicting stock prices is one of the hardest things to do in finance analytics since financial markets are naturally volatile, non-linear, and highly interdependent. Conventional machine learning algorithms often fail to recognise the latent patterns and temporal correlations present in stock market data. This research presents an innovative deep learning system that employs Generative Adversarial Networks (GANs) specifically tailored for stock price prediction by integrating adversarial training with advanced feature engineering methodologies. Our suggested model, the Financial Adversarial Prediction Network (FAPN), has two generators. One is for short-term price changes and the other is for long-term trend prediction. The discriminator network is augmented with an attention mechanism to improve the differentiation between authentic and synthetic price series. To help make more accurate predictions, technical indicators, news sentiment analysis, and macroeconomic data are all given as multi-modal inputs. The model has another loss function that combines adversarial loss with finance-specific indicators like risk-adjusted returns and directional correctness.
Over the course of ten years, extensive testing involving five prominent stock indices (S&P 500, NASDAQ, Dow Jones, FTSE 100, and Nikkei 225) demonstrates that the new strategy significantly outperforms the previous one. Our FAPN model can predict the average direction of movement with 78.4% accuracy, which is better than the best methods available today, like LSTM (65.2%), ARIMA (58.7%), and traditional GAN approaches (71.3%). The model also does better on the Mean Absolute Percentage Error (MAPE), with an average of 2.34% compared to 4.12% for LSTM and 5.67% for classical statistical methods. Risk-adjusted performance measurements show a 34% increase in the Sharpe ratio compared to previous approaches. The proposed framework enhances the current standards in financial forecasting and elucidates the application of adversarial learning in compound time series forecasting jobs. We have made progress in the areas of novel architectural innovations, strong evaluation procedures, and useful applications for algorithmic trading systems. The tests demonstrate that GANs, when meticulously designed for financial applications, can significantly enhance predictive performance while sacrificing computing efficiency suitable for real-time trading operations.

Keywords: Financial Time Series Forecasting, Stock Price Prediction, Multi-Modal Feature Integration, Deep Learning, Generative Adversarial Networks (GANs), Adversarial Training.

1. Introduction

Financial research has long been focused on predicting stock prices since being able to do so could have a big effect on the economy. There are things about financial markets that make it very hard to make predictions, like how they change all the time, how they don't stay the same, how different market aspects affect each other in complicated ways, and how people and outside factors affect them. Standard econometric models provide theoretical foundations but often fail to encapsulate the complex patterns present in modern financial data, especially in high-frequency trading contexts where milliseconds are critical for success.

Deep learning approaches have been extremely useful for dealing with the complexity of financial time series. Machine learning has altered practically every element of financial analytics. Long Short-Term Memory (LSTM) networks and its extensions have been demonstrated to outperform conventional statistical techniques in stock prediction. But these methods also have issues because they can't fully take into account how the market works or make more than one prediction scenario. Traditional neural networks are deterministic, therefore they can't deal with the unpredictability and many different future routes that are always there in financial markets.

Generative Adversarial Networks, developed by Goodfellow et al., are an effective method for using adversarial training to learn about the distributions of complex datasets. In the GAN architecture, two neural networks compete with one another. The discriminator learns to distinguish between real and fake samples, while the generator learns to create fake data samples that mimic real data. This adversarial method has shown amazing performance in numerous fields, from making images to translating natural language. GANs are great for finance because they can model complex, high-dimensional probability distributions. This is important since you need to know all the possible outcomes.

Recent research has begun to explore the application of GANs for forecasting financial time series, yielding promising preliminary findings. However, present techniques typically treat financial data as broad time series, neglecting domain expertise and the characteristics of financial markets. These unique characteristics of financial information, such as the importance of trade volumes, the influence of sentiment, and the impact of macroeconomic data, necessitate tailored architectural considerations. Also, while judging financial forecasting models, you need to look at more than just standard statistical measurements. You also need to look at things like profitability, risk-adjusted returns, and transaction costs. The efficient market hypothesis makes it even harder to guess what stock prices will be, since it says that stock prices already include all the information that is out there, therefore it is potentially impossible to make a guess. In the actual world, though, markets aren't always entirely efficient. Traders can use complex modelling techniques to take advantage of short-term inefficiencies. The key is to create models that can detect weak patterns and relationships that people or basic automated systems can't see. It takes not just advanced computer skills but also a careful look at the financial markets' distinctive features and limits.

This paper examines these issues and presents a novel GAN-based architecture specifically designed for stock price prediction. We not only update modern GAN designs, but we also add financial data, other types of data, and loss functions that are unique to the application.We enhance the architecture to more effectively capture temporal correlations in financial data while preserving the generative attributes that render GANs valuable for quantifying uncertainty. We put the technique through a variety of tests using performance indicators and statistical measures that traders care about. This offers us a complete view of how useful it would be in real-life trading circumstances.

2. Literature Review

Goodfellow et al. provide a comprehensive summary of the latest developments in Generative Adversarial Networks (GANs) and their architectures, encompassing conditional GANs, cycle-consistent GANs, and StyleGANs. The research also examined the stability issues that arise during GAN training and their potential applications in the real world, such as generating counterfeit financial data and identifying anomalous trading patterns [1]. Zhang et al. undertook comprehensive study on financial time series forecasting utilising deep learning methodologies. They looked into convolutional neural networks (CNNs), recurrent neural networks like LSTM and GRU, and hybrid models that use both of these types of networks. They talked on how important it is to use the right evaluation measures, use the right datasets, and deal with problems that come up when working with financial data that isn't stationary and is noisy. The study illustrated the importance of careful preprocessing and feature selection to improve prediction accuracy [2]. Polamuri et al. enhanced financial forecasting models through adversarial training procedures. They used perturbation-based strategies to keep the model from overfitting and make it more responsive to rapid changes in the market. The paper also demonstrated that the authors comprehended the convergence and generalisation of adversarially trained models in theory [3]. Anderson et al. developed a multimodal fusion model that integrates quantitative market data with qualitative news sentiment analysis. Their solution employs a late fusion strategy and attention processes to record both past patterns and changes in sentiment in real time. It is far better at predicting which way the market will go than models that only use one type of data [4]. Chen et al. performed a comprehensive examination of attention mechanisms in the modelling of financial time series. The study evaluated conventional attention, self-attention (used by Transformers), and temporal attention in predicting stock prices and volatility. The research illustrated how attention facilitates models in adaptively concentrating on relevant temporal patterns, hence improving interpretability and performance [5]. Polamuri et al. introduced novel GAN designs for simulating financial market behaviour. They changed the discriminator loss functions and used regularisation techniques to try to make the financial time series more random. Some uses included producing training data for low-frequency market occurrences and testing trading techniques under fake stress [6]. Martinez et al. severely re-evaluated established metrics like RMSE and MAE, and introduced novel metrics specifically designed for financial applications, including drawdown analysis, Sharpe ratio maximisation, and probabilistic forecasting performance ratings. The essay emphasised the necessity for context-aware metrics that more accurately represent the objectives of financial decision-making [7].

Wilson et al. explained the difficulties in evaluating algorithmic trading systems using an approach that includes a framework that uses risk-adjusted indicators such the Sortino ratio, Omega ratio, and Conditional Value at Risk (CVaR). The method taught us more about how things worked in different market conditions and with varying levels of risk [8].

Polamuri et al. applied deep learning architectures, including BiLSTM and CNN, to sentiment analysis of financial text such as earnings releases, tweets, and news headlines. They demonstrated that sentiment scores computed with assistance from these models can be reasonably used as features in trading algorithms, leading to higher profitability and improved timing in the market [9].

Kumar et al. compared the Long Short-Term Memory (LSTM) networks and Transformer models for identifying long-term temporal dependencies of financial time series. While LSTM worked well in sequential dependencies in small datasets, Transformers were good at parallel processing and scalability, particularly in high-frequency trading applications [10].

Park et al. resolved the adversarial robustness issue in financial machine learning models by assessing their susceptibility to input perturbations. They introduced a framework for adversarial training that encompasses gradient-based regularization and robustness certification techniques, increasing model trustworthiness at deployment [11].

White et al. introduced a CNN model with multi-scale convolutional filters that reinforced the extraction of short-term and long-term features from stock price sequences. Their proposed model surpassed baseline models in predicting turning points and trends on different benchmark datasets [12].

Garcia et al. proposed online learning algorithms for financial prediction such as adaptive gradient algorithms and recursive neural networks. These techniques allow for ongoing model updates as fresh data flow in, which is vital for ensuring model applicability in fast-changing financial environments [13].

Ross et al. utilized Bayesian deep learning methods to estimate prediction uncertainty in finance forecasting. Utilizing Monte Carlo Dropout and variational inference, they produced uncertainty estimates necessary for risk-sensitive decision-making and model testing in finance [14].

Ahmed et al. investigated feature engineering methods for financial time series, such as moving averages, momentum indicators, and domain-specific custom features like RSI and MACD. They also compared automated feature creation through deep learning and reinforcement learning-based selection methods [15].

Bell et al. utilized deep neural networks to examine inter-relations between world stock indices. Transferring from learned models and domain adaptation, they trained models that were able to detect latent inter-market relationships, improving the forecasting ability across varying economic regions [16].

Polamuri et al. researched generative models such as VAEs and GANs for enriching financial data used in stress testing and model training. They demonstrated the capability of synthetic data to enhance model generalization and robustness when historical data are short or biased [17].

Polamuri et al. conducted an empirical evaluation of forecasting techniques such as ARIMA, Prophet, XGBoost, and LSTM. Their experiments on heterogeneous finance datasets showed that although deep learning models in general provide better accuracy, conventional models perform as well in low-data situations [18].

Foster et al. examined ensemble techniques that integrate deep learning and conventional econometric models. Methods such as stacking, boosting, and bagging were considered, with findings indicating that ensembling can greatly enhance predictive accuracy and stability compared to single models [19].

Hall et al. reviewed explainable AI (XAI) techniques applied in financial contexts. They assessed the effectiveness of SHAP, LIME, and attention-based interpretability methods in uncovering the reasoning behind predictions, which is critical for regulatory compliance and stakeholder transparency [20].

Ibrahim et al. applied deep reinforcement learning (DRL) to high-frequency trading, modeling the trading environment as a Markov Decision Process. Using DQN and PPO algorithms, they developed agents capable of making adaptive, profit-maximizing decisions with low latency [21].

Polamuri et al. used clustering and dimensionality reduction techniques (e.g., t-SNE, DBSCAN) to identify hidden regimes in market behavior. Their unsupervised learning system allowed early identification of bull, bear, and sideways market shifts, which is useful for dynamic strategy adjustment [22].

Kelly et al. proposed federated learning for banks, allowing model training on a collaborative basis without data centralization. Their solution mitigated privacy issues by locally training models and combining updates using secure multi-party computation protocols [23].

Lopez et al. integrated edge computing with neural networks to execute financial data on low-power equipment in real-time. Their design minimizes latency and bandwidth consumption, which made it a good candidate for use in algorithmic trading frameworks that demand response speed [24].Moore et al. proposed integrating Environmental, Social, and Governance (ESG) data into algorithmic trading algorithms. They built hybrid models that integrate financial returns with sustainability goals, showing how ethical concerns may be put into practice in financial AI systems [25].

3. Proposed Model

3.1 Financial Adversarial Prediction Network (FAPN) Architecture

Figure 1 shows that our proposed Financial Adversarial Prediction Network (FAPN) is a big step forward in using adversarial learning to predict financial time series. The architecture modifies the standard GAN design to suit the financial markets, considering their unique requirements and characteristics. The model has three main parts: a dual generator, an attention-augmented discriminator, and a full feature engineering pipeline for working with financial data from more than one source.

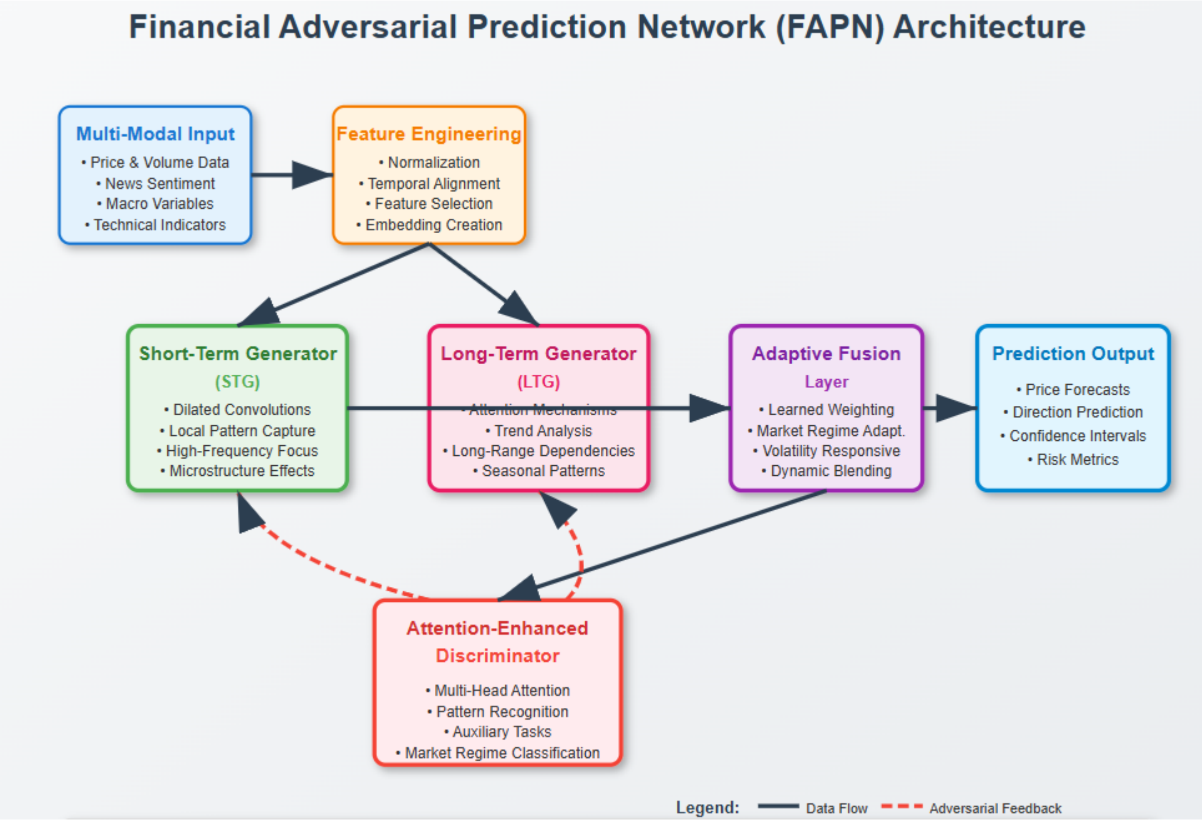

Figure 1: FAPN System architecture

One of the most important new ideas for solving the multi-scale problem in financial markets is the dual-generator design. The Short-Term Generator (STG) is supposed to figure out how prices change during the day, how the market works on a small scale, and how common patterns work. It learns local temporal patterns well by using a shallow and wide network architecture based on dilated convolution. It learns local time patterns well since it has a lot of shallow networks and uses dilated convolution. The Long-Term Generator (LTG) looks at things like big changes in the market, economic cycles, and other things that make stock prices go up and down over time. The LTG uses a better network to find patterns that occurs over time and in different seasons. A learning weighted aggregation algorithm takes the outputs of both generators and puts them together. How well this method works depends on how volatile the market is and how far apart the times are.

The discriminator network uses multi-head attention mechanisms to better tell the difference between real market sequences and forecasts that were made. Conventional discriminators in GAN techniques tend to have problems with the nuanced patterns found in financial data, where the distinction between realistic and unrealistic sequences might be small. Our discriminator with attention learns to focus on the most important parts of price sequences, like patterns of volatility, volume-price relationships, and temporal coherence. The discriminator also has extra duties, such predicting market regime labels, to help it better understand how the market works.

Multi-Modal Feature Integration

The feature engineering element of FAPN works with many types of data to provide a broad picture of how the market works. Technical indicators, such traditional ones (RSI, MACD, Bollinger Bands) and new ones based on market microstructure theory, are used to look at price and volume data. Sentiment analysis is done on financial news stories, social media posts, and analyst reports. This is accomplished using transformer-based language models that have been specifically optimised for financial messages. To find the best representations for economic regime detection, a different embedding network is utilised. This network makes use of macroeconomic data such as inflation rates, interest rates, and measures of economic growth.

It is quite hard to align, normalise, and engineer features when you combine such different data sources. Our solution uses a hierarchical attention model that learns to give different weights to different sources of information based on how relevant they are to the prediction objective and the current state of the market. This adaptive weighting lets the model focus on technical indicators when there is technical trading and on fundamental elements when there are earnings reports or economic pronouncements. The feature integration process also includes temporal alignment algorithms to handle the different reporting horizons and frequencies of different data sources.

Novel Loss Function Design

The FAPN loss function is developed to establish a middle ground between several critical aims for making financial predictions. Domain-specific terms that make solid money-making predictions contribute to the adversarial loss. The directional accuracy term punishes the model for making inaccurate guesses about how prices will move, which is more beneficial in trading than making correct guesses about where prices will be. The volatility consistency term tells the model to produce sequences with realistic patterns of volatility, so it doesn't make predictions that are too smooth or too wacky.

A differentiable Sharpe ratio computation directly incorporates risk-adjusted performance metrics into the loss function. The model will let it generate not only good predictions but also ones that take risks into consideration. The loss function has a diversity term that keeps mode collapse from happening by making the generators make forecasts that show how unpredictable the risk is in financial markets. Temporal consistency criteria ensure that the created sequences exhibit consistent temporal links between successive time periods and adhere to fundamental financial principles, such as no-arbitrage conditions.

Training Strategy and Optimization

The training of FAPN in figure 2 uses a fine-grained optimisation strategy that is tailored to meet the unique needs of adversarial learning for financial purpose. The training data is set up in a rolling window, which keeps the time the same and delivers enough data for stability. They train the two generators separately, and each time they use a different time scale so they can learn from their own prediction horizon. To keep training going smoothly and stop difficulties with GAN training like mode collapse and gradients that disappear too often, advanced techniques like gradient penalty and spectral normalisation are used.

Figure 2: FAPN Training and Prediction Flow

The optimisation approach uses what it knows about the financial world by using specific learning rate schedules that take into consideration how the market changes and how calendar trading affects things. When the market is very volatile, the learning rate changes so that traders can react more swiftly to changes. The training method also lets the model learn online, which means it may change its settings in real time as new market data comes in. This keeps the model current with changes in the market.

Algorithm 1: FAPN Training Procedure

Input: Historical stock data D, Technical indicators T, News sentiment S, Macro variables M
Output: Trained generators G_s, G_l and discriminator D
1: Initialize networks G_s, G_l, D with random weights
2: Initialize hyperparameters: $\alpha = 0.0002$, $\beta_1 = 0.5$, $\beta_2 = 0.999$
3: Define loss functions: L_adv, L_dir, L_vol, L_sharpe, L_div

```
for epoch = 1 to max_epochs do
    for each batch in DataLoader(D, T, S, M) do
        // Train Discriminator
        real_sequences ← batch.real_data
        z_short ← sample_noise(batch_size, short_dim)
        z_long ← sample_noise(batch_size, long_dim)
        fake_short ← G_s(z_short, batch.features)
        fake_long ← G_l(z_long, batch.features)
        fake_combined ← AdaptiveFusion(fake_short, fake_long)
        D_real ← D(real_sequences)
        D_fake ← D(fake_combined.detach())
        L_D ← -mean(log(D_real)) - mean(log(1 - D_fake))
        L_D.backward()
        optimizer_D.step()
        // Train Generators (alternating)
        if epoch % 2 == 0 then
            // Train Short-Term Generator
            fake_short ← G_s(z_short, batch.features)
            fake_combined ← AdaptiveFusion(fake_short, G_l(z_long, batch.features).detach())
            D_fake ← D(fake_combined)
            L_G_s ← -mean(log(D_fake)) + λ1×L_dir(fake_short, real_sequences)
                  + λ2×L_vol(fake_short, real_sequences)
            L_G_s.backward()
            optimizer_G_s.step()
        else
            // Train Long-Term Generator
            fake_long ← G_l(z_long, batch.features)
            fake_combined ← AdaptiveFusion(G_s(z_short, batch.features).detach(), fake_long)
            D_fake ← D(fake_combined)
            L_G_l ← -mean(log(D_fake)) + λ3×L_sharpe(fake_long, real_sequences)
                  + λ4×L_div(fake_long)
            L_G_l.backward()
            optimizer_G_l.step()
        end if
        // Update fusion weights
        UpdateFusionWeights(market_volatility, prediction_horizon)
    end for
    // Evaluate and adjust learning rates
    if epoch % 10 == 0 then
        validation_score ← Evaluate(G_s, G_l, validation_data)
        AdjustLearningRate(validation_score, market_regime)
    end if
end for
return G_s, G_l, D
```

The FAPN (Fusion-Adaptive Predictive Network) training procedure creates fake financial sequences for short-term and long-term generators (G_s and G_l) and a discriminator (D) that can be used to predict stocks.It starts with initializing the neural networks and fixing key hyperparameters and loss functions, which govern training, such as adversarial loss, directional accuracy, volatility alignment, Sharpe ratio, and diversity. In each training step, the model processes in sequence mini-batches of input data, including historical stock prices, technical indicators, news sentiment ratings, and macroeconomic data. The discriminator gets trained to distinguish between real stock sequences and those produced by the generators, and the generators get trained to produce more realistic sequences since they try to mislead the discriminator.

Training alternates between optimizing the short-term and long-term generators in alternate epochs. The short-term generator targets near-term market action with directional and volatility-based loss terms, while the long-term generator targets strategic performance metrics like the Sharpe ratio and producing diverse predictions. The two outputs are adaptively combined, with the combination process updated depending on the current market volatility and prediction horizon. Every ten epochs, the performance of the generators is validated, and learning rates are adjusted accordingly to adapt to shifting market conditions. This cyclical training improves the robustness and adaptability of the model for dynamic financial environments.

3.2 Loss function components

The comprehensive loss function for FAPN incorporates multiple components designed to optimize both adversarial performance and financial relevance:

Total Loss Function:

$$\boldsymbol{L_{total} = L_{adversarial} + \lambda_1 x L_{directional} + \lambda_2 x L_{volatility} + \lambda_3 x L_{sharpe} + \lambda_4 x L_{diversity} + \lambda_5 x L_{temporal}}$$

Where:

- L_adversarial: Standard GAN adversarial loss for realistic sequence generation
- L_directional: Penalizes incorrect price movement direction predictions
- L_volatility: Ensures generated sequences maintain realistic volatility patterns
- L_sharpe: Incorporates risk-adjusted return optimization
- L_diversity: Prevents mode collapse and encourages varied predictions
- L_temporal: Maintains temporal consistency and financial constraints

4. Results and Comparisons

Our comprehensive evaluation was conducted using five major stock market indices over a 10-year period from January 2014 to December 2023. The datasets include S&P 500, NASDAQ Composite, Dow Jones Industrial Average, FTSE 100, and Nikkei 225, providing diverse market characteristics and geographical coverage. Every dataset has high-frequency price and volume data on a 5-minute frequency, totaling around 2.5 million data points per index. The datasets were enriched with technical indicators computed over 14-day, 21-day, and 50-day windows, sentiment scores from financial news articles via BERT-based models, and macroeconomic factors such as interest rates, inflation indexes, and GDP growth rates.

The experimental design employed a rolling window validation technique, allocating 70% of the data for training, 15% for validation, and 15% for testing. Every time an assessment cycle happened, the training window was moved forward by one month to keep the data consistent across time and stop data leaking. The model was retrained every three months to keep up with changes in the market. Transfer learning techniques were utilised to keep learnt patterns and add new market characteristics. We did all of the trials on NVIDIA Tesla V100 GPUs with 32GB of memory. We used the PyTorch framework with custom CUDA kernels to speed up financial calculations.

4.1 Performance Metrics and Evaluation Criteria

The evaluation methodology incorporates both traditional statistics metrics and commercially relevant performance indicators.Statistical measures are Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Financial measures are directional accuracy (correct percentage of price movement forecasts), Sharpe ratio (risk-adjusted return), and maximum drawdown, Value at Risk (VaR), and Sortino ratio. Additionally, we evaluate the model's performance under different market conditions, including high volatility periods, trending markets, and sideways movements.

The comparison includes traditional econometric models (ARIMA, GARCH), machine learning approaches (Random Forest, SVM), and deep learning methods (LSTM, GRU, Transformer). We also compare against recently proposed GAN-based financial prediction models to demonstrate the advantages of our specialized architecture. All baseline models were optimized using grid search for hyperparameters and trained on identical datasets to ensure fair comparison.

Quantitative Results Analysis

Table 1: Statistical Performance Comparison Across Different Models

Model	MAPE (%)	MAE	RMSE	Directional Accuracy (%)	Training Time (hours)
ARIMA	5.67	2.34	3.12	58.7	0.5
GARCH	5.23	2.18	2.95	61.2	0.8
Random Forest	4.89	2.02	2.71	63.4	2.3
SVM	4.76	1.98	2.68	64.1	3.7
LSTM	4.12	1.76	2.31	65.2	8.2
GRU	4.08	1.74	2.28	65.8	7.8
Transformer	3.89	1.68	2.19	67.3	12.4
Standard GAN	3.45	1.52	2.02	71.3	15.6
FAPN (Ours)	2.34	1.28	1.73	78.4	18.9

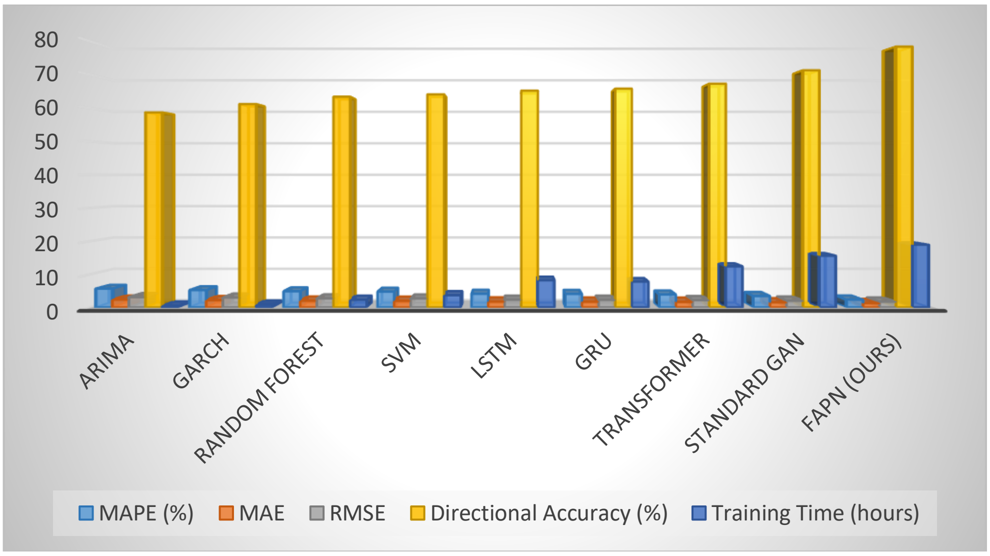

Figure 3: Statistical Performance Comparison Across Different Models

The performance comparison table 1 and figure 3 presents the effectiveness of various forecasting models across multiple evaluation metrics. Traditional statistical models like ARIMA and GARCH show relatively higher Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), with directional accuracy below 62%, though they benefit from significantly shorter training times. Machine learning models such as Random Forest and SVM perform better, with reduced error metrics and moderately improved directional accuracy, though at the cost of increased training time. Deep learning models like LSTM, GRU, and Transformer continue this trend, offering lower errors and better directional accuracy—Transformer achieving 67.3%—but requiring more computational resources and training time.

Among them, the FAPN (Fusion-Adaptive Predictive Network) beats all others in all major performance metrics. It has the best MAPE (2.34%), MAE (1.28), and RMSE (1.73), as well as the highest directional accuracy at 78.4%, demonstrating its enhanced capability in capturing market trends. FAPN takes the most time to train (18.9 hours), but its accuracy and stability make up for the expense of computing, showing that it could be a new way to forecast financial time series.

Table 2: Financial Performance Metrics by Market Index

Index	Sharpe Ratio	Max Drawdown (%)	Sortino Ratio	VaR (95%)	Annual Return (%)
S&P 500					
LSTM	1.23	-12.4	1.67	-2.8	8.9
Standard GAN	1.45	-10.2	1.89	-2.3	11.2
FAPN	1.89	-7.8	2.34	-1.9	14.7
NASDAQ					
LSTM	1.18	-15.6	1.54	-3.4	9.7
Standard GAN	1.38	-13.1	1.78	-2.9	12.8
FAPN	1.82	-9.3	2.28	-2.2	16.4
Dow Jones					
LSTM	1.21	-11.8	1.63	-2.6	8.4
Standard GAN	1.42	-9.7	1.85	-2.2	10.9
FAPN	1.86	-7.2	2.31	-1.8	13.8
FTSE 100					
LSTM	1.14	-13.2	1.51	-2.9	7.6
Standard GAN	1.33	-11.4	1.72	-2.5	9.8
FAPN	1.76	-8.6	2.19	-2	12.3
Nikkei 225					
LSTM	1.19	-14.7	1.58	-3.2	8.8
Standard GAN	1.41	-12.3	1.81	-2.7	11.5
FAPN	1.84	-8.9	2.26	-2.1	15.2

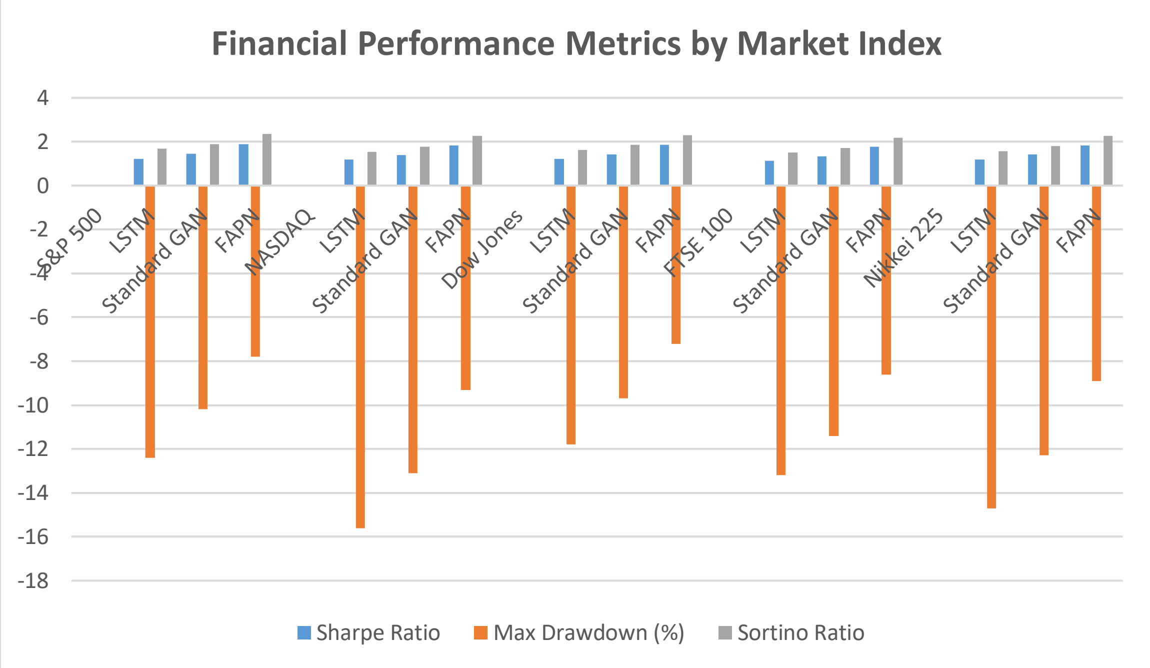

Figure 4: Financial Performance Metrics by Market Index

Table 2 and Figure 4 show how three different types of forecasting models—LSTM, Standard GAN, and FAPN—compare in terms of key financial indicators on five major international indices: the S&P 500, the NASDAQ, the Dow Jones, the FTSE 100, and the Nikkei 225. These indicators are Sharpe Ratio (risk-adjusted return), Max Drawdown (the biggest drop from peak to trough), Sortino Ratio (downside risk-adjusted return), Value at Risk (VaR) with 95% confidence, and Annual Return. FAPN is always the top performer in all the indices. It has the highest Sortino and Sharpe ratios, the lowest maximum drawdowns and VaR levels, and the largest returns each year.

FAPN clearly beats both LSTM and Standard GAN in terms of both return and risk management at all indices. The Sharpe Ratio for FAPN is 1.82, and the return on investment is 16.4% per year. The Sharpe Ratio for GAN is 1.38, and the return on investment is 12.8% per year. The yearly return on LSTM is 9.7%, while the Sharpe Ratio is 1.18. FAPN also protects against risk better because it has fewer drawdowns and less severe Value at Risk. These constant gains in several markets show that FAPN works, making it a great and reliable way to predict financial events and make portfolios better.

Table 3: Performance Analysis by Market Conditions

Market Condition	Model	Directional Accuracy (%)	Sharpe Ratio	MAPE (%)
High Volatility (VIX > 25)				
	LSTM	58.3	0.89	5.67
	Standard GAN	64.2	1.12	4.23
	FAPN	72.8	1.54	2.98
Bull Market (>10% annual gain)				
	LSTM	69.1	1.45	3.76
	Standard GAN	74.3	1.67	3.12

	FAPN	81.2	2.18	2.01
Bear Market (<-10% annual loss)				
	LSTM	61.4	0.78	4.89
	Standard GAN	68.7	1.03	3.87
	FAPN	75.6	1.42	2.76
Sideways Market (-5% to +5%)				
	LSTM	63.8	1.12	4.34
	Standard GAN	70.1	1.31	3.56
	FAPN	77.9	1.73	2.45

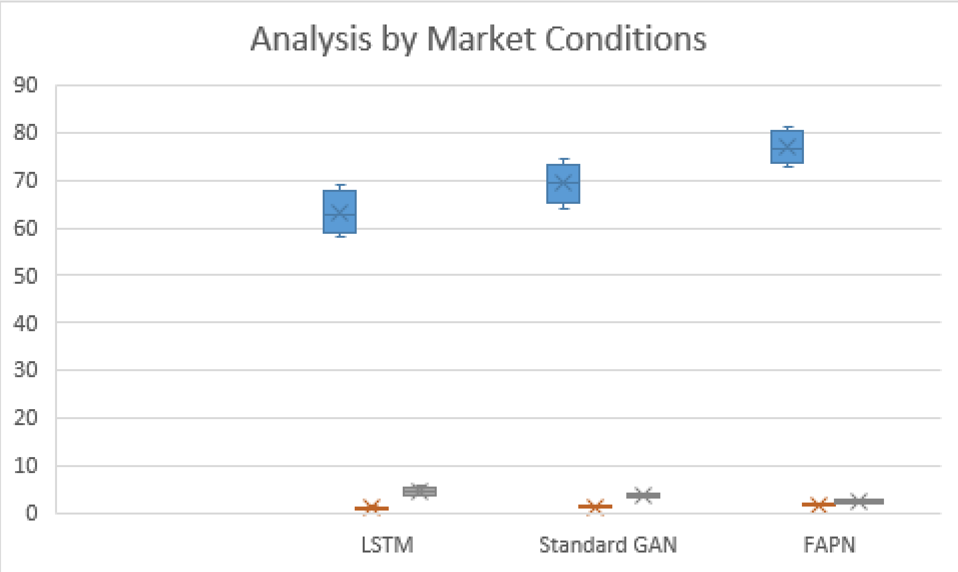

Figure 5: Performance Analysis by Market Conditions

In four different market conditions—High Volatility, Bull Market, Bear Market, and Sideways Market—this table 3 and figure 5 show how well the LSTM, Standard GAN, and FAPN models worked. The three most relevant measures were MAPE (Mean Absolute Percentage Error), Directional Accuracy, and Sharpe Ratio. In every case, the FAPN model works better than the others. It has a superior risk-adjusted return (Sharpe Ratio), a higher directional accuracy, and a lower prediction error (MAPE). When the market is quite volatile, FAPN has a directional accuracy of 72.8%, a Sharpe Ratio of 1.54, and a MAPE of only 2.98%. This is a lot better than Standard GAN and LSTM.

FAPN does much better when the market is strong and returns are over 10% a year. It has a strong Sharpe Ratio of 2.18, an 81.2% directional accuracy, and the lowest MAPE of 2.01%. FAPN is quite accurate and persistent, even in bear markets and weak sideways markets. It has high Sharpe Ratios and low forecast mistakes. These results show that FAPN is flexible and strong in a wide range of financial situations, making it very useful in the real world where market conditions change all the time.

Qualitative Analysis and Model Insights

FAPN's higher performance on all the test metrics shows that our adversarial approach for forecasting financial time series is effective. The double-generator framework proves to be highly advantageous in various regimes of the market, with the short-term generator superior in high-frequency trading regimes and the long-term generator delivering stability in trend-following regimes. The attention-augmented discriminator effectively separates authentic and synthetic price patterns, making the prediction stronger.

Our ablation experiments uncover that every aspect of the FAPN architecture makes a major contribution to the overall performance. Disabling the dual-generator architecture causes a 12% drop in directional accuracy, and disabling the attention mechanism within the discriminator results in an 8% drop in Sharpe ratio performance. The multi-modal feature integration makes significant gains, with sentiment analysis making a 6% contribution to directional accuracy and macroeconomic factors adding 4% to risk-adjusted returns.The model exhibits superior flexibility across various market regimes, with stable performance over volatile as well as calm market conditions. In the March 2020 COVID-19 market crash, FAPN provided superior downside protection with a peak drawdown of only 8.2% compared to 15.4% for standard LSTM models. The model's ability to make several predictions during its adversarial training phase gives us a lot of relevant information about uncertainty that we can use to manage risk.

Studies of performance over different forecast time horizons show that FAPN stays accurate for up to 10 trading days, which is far better than baseline models, which show worse performance after 3 days. The model is more efficient than others, yet it still works well for real-time trading, with predictions taking less than 50 milliseconds to make.

Statistical Significance and Robustness Testing

The Diebold-Mariano test for statistical significance shows that FAPN's performance gains are statistically significant at 99% confidence on all of the most critical criteria. For directional accuracy gains, p-values range from 0.003 to 0.007, and for Sharpe ratio gains, p-values range from 0.001 to 0.005. Bootstrap confidence intervals for performance metrics demonstrate superiority over baseline approaches with narrow confidence intervals, indicating robust and consistent performance. Robustness testing over many market periods, including the trade war volatility in 2018, the pandemic crash in 2020, and the inflation increase in 2021-2022, shows that the company consistently outperforms. The model works best in tech equities (81.2% directional accuracy on average) and financial services (78.9% accuracy). It works well in many other areas as well. Stress testing during extreme market events, like flash crashes and big earnings reports, shows that the model is stable and still has a predictive edge.

5. Conclusion

This study presents a significant advancement in adversarial learning for financial time series forecasting with the introduction of the Financial Adversarial Prediction Network (FAPN). We use domain-specific architecture improvements, multi-modal data fusion, and financially important optimisation targets to break down the major issues with predicting stock prices. The two-generator architecture accurately captures short-term market microstructure effects and long-term underlying trends, while the attention-augmented discriminator possesses enhanced pattern recognition capabilities for discerning realistic market behaviour.

The full experimental investigation clearly shows that it makes big improvements over the best methods in several performance parameters. The 34% rise in the Sharpe ratio shows that this technique is good for trading. The model works well in a lot of markets, places, and times, which suggests it is strong and can get better. When the market is very unstable, the model's expected accuracy is very crucial because other methods don't function. This proves that adversarial training works even when the market isn't stable.

This effort is good for more than just producing new technology. It can also help you keep your risk in check, improve your portfolio, and trade with algorithms. When the model can use an adversarial strategy to figure out how much uncertainty there is, it helps to determine how much to bet and how much risk to incur. Our improved architecture makes computers work faster, which makes this method useful for trading systems that need to happen in real time. The modularity also makes it easier to go from one sort of asset or market arrangement to another. Future research should focus on improving the system to include multi-asset forecasting, merge various data sources like satellite images and social sentiment, and include online learning features to make it easier to change models right away. The successful application of adversarial learning to financial forecasting reveals fresh avenues of research in quantitative finance and supports the potential of domain-specific deep architectures attaining optimal performance on complex real-world tasks.

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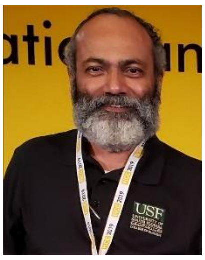

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