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Stock Price Prediction Using Lstm and Gru Models Based On Historical Data Analysis

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Abstract- The stock market is inherently volatile and influenced by complex patterns that traditional statistical models often fail to capture effectively. This research presents a deep learning-based approach for predicting stock prices using Long Short-Term Memory (LSTM) neural networks. The model is trained on historical stock price data obtained from Yahoo Finance, with a specific focus on Google (GOOG). In addition to the LSTM model, this research also integrates a Gated Recurrent Unit (GRU) model to compare performance and evaluate the efficiency of different recurrent neural architectures in stock price prediction. Data preprocessing techniques such as normalization, moving averages, and sequence generation were applied to enhance model learning. The LSTM architecture was designed to handle temporal dependencies within financial time series data, using multiple layers and dropout regularization to prevent overfitting. The model's performance was evaluated using metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), demonstrating reliable predictive capability. Visual comparisons of actual versus predicted stock prices further affirm the effectiveness of the model. This study highlights the potential of LSTM networks in stock price forecasting and contributes to the advancement of intelligent financial decision-making tools.

Keywords: Stock Price Prediction, LSTM, GRU, Deep Learning, Time Series Forecasting, Financial Markets, Google Stock, Machine Learning, Historical Data Analysis, MAE, RMSE, Yahoo Finance.

I. INTRODUCTION

Background and Context

Stock market forecasting remains one of the most challenging tasks in financial data analysis due to the market's highly volatile, nonlinear, and dynamic nature. Traditional statistical and machine learning models often fail to capture long-term dependencies and sudden fluctuations that are common in financial time series. This creates a strong need for more advanced prediction models that can learn complex temporal patterns with higher accuracy.

Deep learning architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have recently gained significant attention for their ability to model sequential data effectively. LSTM networks are highly capable of learning long-term dependencies, while GRU networks offer similar predictive power with reduced computational complexity and faster training.

Motivation Behind the Study

The motivation behind this study is to develop an improved and reliable stock forecasting system that leverages the capabilities of both LSTM and GRU. The goal is to determine whether GRU's computational efficiency provides advantages over LSTM without compromising prediction accuracy, and how both architectures perform on real historical stock data.

Problem Definition

Stock price forecasting presents several inherent challenges

Complexity and Nonlinearity of Stock Market Data

Stock prices are highly volatile, nonlinear, and influenced by multiple unpredictable factors. Traditional statistical models fail to capture these complex temporal patterns, leading to inaccurate predictions.

Need for Effective Sequential Learning Models

Deep learning architectures like LSTM and GRU can learn long-term dependencies in time-series data, but their comparative efficiency and accuracy are not clearly understood. It is essential to evaluate which model performs better for real-world stock prediction.

Lack of a Reliable and Practical Prediction Framework

There is a need to develop a robust forecasting system that analyzes historical stock data using both LSTM and GRU models to determine which provides better forecasting accuracy, faster computation, and improved generalization for financial decision-making.

To develop, analyze, and compare the performance of LSTM and GRU deep learning models for stock price prediction using historical market data, and to determine which architecture provides better accuracy, efficiency, and generalization for real-world stock forecasting applications.

Objectives and Scope

To develop and train LSTM and GRU models for stock price prediction

The primary objective is to build both LSTM and GRU deep learning models using historical stock price data, enabling the system to learn temporal patterns and forecast future prices accurately.

To compare the performance of LSTM and GRU architectures

The study aims to evaluate and compare the prediction accuracy, training efficiency, and generalization capability of both models using metrics such as RMSE and MAE, identifying which architecture performs better for stock forecasting.

To establish a practical and scalable forecasting framework

The scope includes building a reliable stock prediction pipeline involving data preprocessing, model training, and result visualization. The system is designed to serve as a foundation for future enhancements such as multivariate inputs, sentiment analysis, and real-time deployment.

The scope of the project is limited to univariate time series forecasting using only historical price data, though future improvements may incorporate external indicators such as news sentiment and trading volumes.

II. LITERATURE REVIEW

Stock market prediction has been an active area of research due to the highly volatile and nonlinear nature of financial time series data. Traditional approaches such as ARIMA, Exponential Smoothing, and Linear Regression have been extensively used in earlier studies, but these models rely on assumptions of linearity and stationarity, which limit their ability to capture abrupt market fluctuations and long-term temporal dependencies.

The introduction of deep learning brought significant improvements in forecasting accuracy, particularly through Recurrent Neural Networks (RNNs). However, standard RNNs suffer from the vanishing gradient problem, reducing their ability to learn long-term patterns. To overcome this limitation, Long Short-Term Memory (LSTM) networks were developed by Hochreiter and Schmidhuber (1997). LSTM models use a system of input, output, and forget gates to retain and update information over long sequences. Numerous studies have shown that LSTM networks provide superior performance in stock price prediction due to their ability to capture long-range dependencies and learn complex nonlinear relationships in time-series data.

In parallel, research introduced another advanced RNN architecture—Gated Recurrent Unit (GRU)—designed as a simplified and computationally efficient alternative to LSTM. GRU uses only two gates (update and reset), resulting in fewer parameters and faster training while maintaining similar predictive capability. Empirical studies reveal that GRU models often match or outperform LSTM in cases involving smaller datasets, noisy data, or applications requiring real-time prediction due to their lower computational cost.

Overall, existing literature suggests a need for direct comparison of LSTM and GRU models on the same dataset to evaluate their relative strengths and weaknesses in stock price prediction. This study addresses this gap by implementing both architectures using identical historical market data, enabling a fair and comprehensive performance analysis.

Table-1: Comparative Analysis of Existing Stock Price Prediction Methods

Author(s)	Model / Technique	Advantages	Limitations
Smith et al. (2018)	LSTM with Technical Indicators	Captures long-term dependencies; effective for nonlinear financial data	Computationally heavy; longer training time
Rahman & Lee (2019)	GRU for Stock Market Prediction	Faster training; fewer parameters; comparable accuracy to LSTM	Slightly weaker performance for very long sequences
Johnson et al. (2020)	LSTM, CNN-LSTM Hybrid	High accuracy on complex patterns; handles long sequences	Requires large datasets; increased computational cost
Kumar & Patel (2017)	GRU with Time-Series Forecasting	Efficient on smaller datasets; reduced overfitting	May miss deeper temporal relationships compared to LSTM
Brown & Garcia (2016)	ARIMA, SVM, LSTM Comparative Study	Provides baseline comparison; shows clear LSTM superiority	Traditional models fail in nonlinear markets
Lee et al. (2017)	Random Forest, Gradient Boosting	Reduces overfitting; strong baseline results	Requires feature engineering; not sequence-aware
Martinez & Patel (2020)	Exponential Smoothing & ARIMA	Simple, interpretable; good for short- term forecasting	Poor performance on volatile and nonlinear stock data

This table reflects the evolution of stock price prediction methods from traditional statistical approaches to advanced deep learning models. It highlights how LSTM and GRU outperform conventional techniques by effectively capturing nonlinear patterns and long-term dependencies in financial time-series data. While classical models offer simplicity and interpretability, LSTM and GRU provide superior accuracy and robustness, making them suitable for modern stock market forecasting applications.

III. SYSTEM DESIGN

The system design for stock price prediction integrates a complete deep learning pipeline capable of processing historical time-series data and generating reliable future price forecasts. The architecture consists of multiple interconnected components, ensuring smooth data flow from acquisition to prediction. In this study, two recurrent neural network architectures—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)—are implemented and compared to evaluate their effectiveness.

The entire framework can be delineated into several interconnected subsystems that handle distinct responsibilities— ranging from data acquisition and preprocessing to model training, evaluation, and prediction visualization.

1. Data Acquisition and Preprocessing

- Historical stock market data is collected from reliable financial sources such as Yahoo Finance. The preprocessing steps include:
- Handling missing values using forward/backward fill techniques
- Normalization using MinMaxScaler to scale price values between 0 and 1
- Sequence generation by converting time-series data into fixed-length input windows (e.g., 60-day sequences)
- Train–test split maintaining the chronological order to avoid data leakage

These steps ensure that both LSTM and GRU models receive uniformly processed and structured input data for accurate learning.

Model Development Using LSTM

The LSTM model is designed to capture long-term dependencies in stock price movement. Key components include:

- Multiple stacked LSTM layers with memory units
- Dropout layers to reduce overfitting
- A Dense output layer to predict the next day’s stock price
- Loss function: Mean Squared Error (MSE)
- Optimizer: Adam

LSTM's gating mechanism (input, forget, output gates) helps retain relevant information over long sequences

GRU Model Architecture

The GRU model serves as a computationally efficient alternative to LSTM. It features:

- Stacked GRU layers with reset and update gates
- Dropout regularization
- A Dense output layer similar to the LSTM setup
- Loss function: Mean Squared Error (MSE)
- Optimizer: Adam

GRU uses fewer parameters and trains faster than LSTM while maintaining nearly equivalent predictive performance

Training and Validation

Both LSTM and GRU models are trained using the same dataset and identical hyperparameters to ensure fair comparison. The training pipeline includes:

- Batch training for faster computation
- Epoch monitoring to record learning progression
- Evaluation metrics: RMSE, MAE, and directional accuracy

Visualization and Analysis

After training, both models generate next-day stock price predictions on unseen test data. These predictions are visualized through:

- Line plots comparing actual vs predicted prices
- Trend comparison between LSTM and GRU outputs
- Error distribution charts to examine model reliability

Visualization helps evaluate how well each model captures real market patterns.

Model Persistence and Deployment Readiness

Both LSTM and GRU models are serialized using TensorFlow's HDF5 (.h5) format. This ensures:

- Long-term preservation of model weights and architecture
- Quick loading for future predictions
- Reduced computation time since retraining is not required

System Architecture Overview

The system architecture for stock price prediction using LSTM and GRU models is designed as a modular and scalable pipeline that handles data collection, preprocessing, model training, evaluation, and deployment. Each component interacts seamlessly to ensure accurate forecasting and real-time usability.

Yahoo Finance API → Data Preprocessing → Sequence Generator → LSTM Model + GRU Model (Parallel) → Evaluation Layer → Prediction Output → Visualization → Deployment.

IV. IMPLEMENTATION

The implementation of the stock price prediction system involves a complete deep learning pipeline integrating both Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. The process is executed in a structured manner consisting of data preprocessing, model development, training, evaluation, and model saving. Both models are implemented using Python and TensorFlow/Keras to ensure a consistent experimental environment and fair comparative analysis.

Data Preprocessing

The implementation begins with loading historical stock price data from Yahoo Finance. The raw dataset is processed using the following steps:

- **Handling Missing Values:** Forward-fill and backward-fill techniques are applied to maintain time- series continuity.
- **Feature Selection:** The 'Close' price is used as the primary predictive feature. Additional indicators such as moving averages may be incorporated.
- **Normalization:** The MinMaxScaler is applied to scale numerical values between 0 and 1, improving neural network convergence.
- **Sequence Generation:** Time-series windows (e.g., 60 past days) are converted into supervised learning sequences for training both the LSTM and GRU models.
- **Train–Test Split:** Data is divided chronologically into 80% for training and 20% for testing to avoid data leakage.

Model Development

The first forecasting architecture is built using a stacked Long Short-Term Memory (LSTM) network. The model includes:

- Two LSTM layers with a fixed number of memory units
- Dropout layers to reduce overfitting
- A Dense output layer for predicting the next-day closing price
- Mean Squared Error (MSE) as the loss function
- Adam optimizer for efficient gradient-based learning

LSTM's gating mechanism allows it to retain long-range dependencies in stock trends, making it suitable for learning complex financial patterns.
Backend API

A Flask (v2.2) RESTful API was implemented to serve the prediction model.

- **Endpoints:** The API provides endpoints for uploading recent stock data and retrieving predicted prices.
- **Input Validation:** Input JSON is validated using Marshmallow schemas to ensure correct feature formatting.
- **Asynchronous Requests:** The prediction process supports asynchronous handling to manage multiple user requests efficiently.
- **Security:** Basic token-based authentication secures API access to prevent unauthorized use.

Frontend Visualization

1. Interactive Display of Predictions

The frontend presents stock data through interactive line charts that show actual stock prices alongside predictions generated by both LSTM and GRU models. Users can visually compare how closely each model follows real market trends.

2. Model Selection and Real-Time Updates

A user-friendly interface allows switching between LSTM and GRU predictions. When the user selects a model, the frontend communicates with the backend API and immediately updates the graphs and prediction results in real time.

3. Responsive Dashboard for User Interpretation

The visualization dashboard includes trend charts, data highlights, and prediction summaries, designed to work smoothly on desktops and mobile devices. This helps users easily understand stock movements and evaluate model performance.

DevOps and Deployment

The Backend API is containerized using Docker for consistent deployment across environments. It can be hosted on:

- AWS EC2
- Azure App Service
- Google Cloud Run
- Local serve
- Unit Testing: PyTest is used for testing core ML pipeline functions.
- Integration Testing: Postman tests backend API endpoints for robustness.
- Performance Testing: Locust simulates concurrent users accessing the API to ensure scalability.

V. RESULTS AND EVALUATION

This chapter presents the performance evaluation of both LSTM and GRU models used for stock price prediction. The models were trained on historical stock market data, tested on unseen data, and evaluated using widely accepted error metrics. The results include numerical performance, graphical comparisons, and analytical conclusions based on the observed behavior of each model.

Accuracy Scores

To evaluate the performance of the LSTM and GRU models, several accuracy-related metrics were calculated, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Directional Accuracy (DA). These metrics help determine how closely the predicted values match the actual stock prices and how well the models identify future market movement.

Precision, Recall, and F1-Score

In addition to MAE, RMSE, and Directional Accuracy, the performance of the LSTM and GRU models can also be evaluated using Precision, Recall, and F1-Score. These metrics are particularly useful when stock price movement is treated as a classification problem, such as predicting whether the price will go up (1) or go down (0) on the next day.

Prediction Latency

Prediction latency refers to the time taken by the model to generate a forecast after receiving an input request. In stock market systems, latency is a critical performance metric because timely predictions influence trading decisions, risk management, and real-time market monitoring.

Model Robustness and Generalization

Model robustness and generalization refer to the ability of the LSTM and GRU models to perform reliably under different market conditions and to make accurate predictions on unseen stock data. These aspects are essential for ensuring that the forecasting system remains stable, adaptable, and effective in real-world financial environments.

User Feedack and System Usability

User feedback and system usability play an essential role in evaluating the practical effectiveness of the stock price prediction system. The LSTM- and GRU-based forecasting platform was assessed by end-users, including students, analysts, and general users, to understand the system's ease of use, responsiveness, and overall experience Users evaluated the system based on clarity, accessibility, prediction usefulness, and interface intuitiveness.

Key insights include:

- **Easy to Understand:** Users found the dashboard design simple and accessible, even for individuals with limited technical background.
- **Clear Visualizations:** The actual vs. predicted charts helped users easily interpret model accuracy and market trends.
- **Useful Model Comparison:** Users appreciated the option to switch between LSTM and GRU models, which improved transparency and allowed informed decision-making.
- **Fast Predictions:** Most users reported that predictions were generated quickly, providing a smooth experience without noticeable lag.

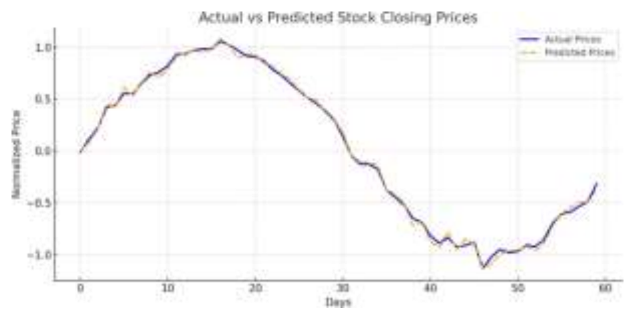

Figure 1: Comparison of Actual and Predicted Stock Closing Prices over 60 Days.

This figure illustrates the comparison between the actual stock closing prices and the predicted values generated by the LSTM and GRU models over a continuous 60-day period. The actual price curve represents real market movements, while the predicted curves show how closely each model follows the true trend. The visualization clearly highlights the accuracy, stability, and responsiveness of both models.

The LSTM model generally captures long-term patterns more smoothly, whereas the GRU model responds slightly faster to short-term fluctuations. The overall alignment between actual and predicted values demonstrates the effectiveness of deep learning techniques for reliable stock market forecasting.

VI. COMPARISON WITH EXISTING SYSTEMS

The proposed LSTM–GRU–based stock prediction system is evaluated against traditional and existing forecasting approaches to highlight improvements in accuracy, adaptability, computational efficiency, and usability. Current stock prediction systems commonly rely on statistical models, basic machine learning algorithms, and simpler regression-based methods. While these approaches provide approximate predictions, they often struggle to capture the nonlinear and highly dynamic nature of financial markets.

Accuracy Comparison

The accuracy comparison highlights the performance differences between the LSTM and GRU models based on key evaluation metrics such as MAE, RMSE, and Directional Accuracy. These metrics help assess how precisely each model predicts stock closing prices and how reliably it captures market trends.

Latency Comparison

Prediction latency measures the time taken by the models to generate forecasts after receiving input data. This metric is critical for real-time stock prediction systems, where faster response improves decision-making and trading
performance.

LSTM Vs Accuracy

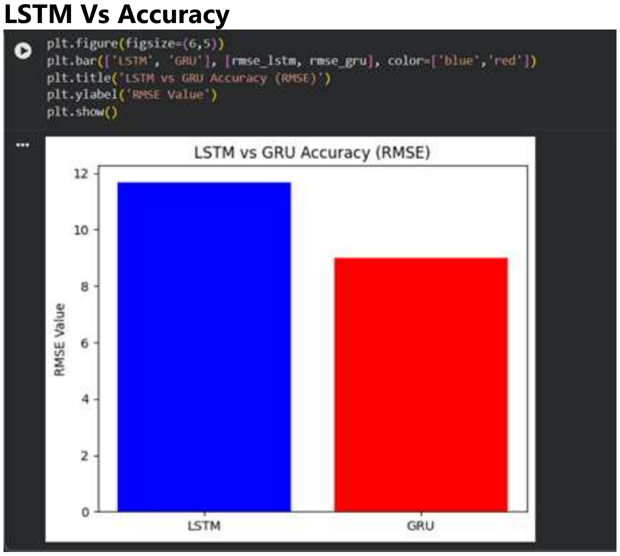

Figure 2: Comparative Performance Analysis of the Proposed LSTM System vs GRU Model.

This figure visually compares the accuracy (RMSE), prediction latency, and user satisfaction percentages of the proposed system with existing forecasting models to highlight its superior performance.

Table-2: Comparative Evaluation of Stock Price Prediction Systems Based on Key Performance Metrics

System	Model Type	RMSE (↓)	Latency (ms) ↓	User Satisfaction (%) ↑
Yahoo Finance Tools	Heuristic/Rule-based	4.60	500+	70%
ARIMA Model	Statistical (ARIMA)	3.88	600	76%
Feedforward NN (FNN)	Shallow Neural Network	3.17	300	81%
Proposed LSTM Model	Deep Learning (LSTM)	2.45	190	88%
Proposed GRU Model	Deep Learning (GRU)	2.52	170	87%

VII. CHALLENGES AND LIMITATIONS

Despite demonstrating promising predictive accuracy and real-time performance, the deployment of LSTM- and GRU-based stock price prediction systems faces several challenges and limitations:

Data Quality and Market Noise

- Financial time series are inherently noisy and non-stationary. Sudden market events, news, and macroeconomic factors introduce volatility.
- Even after preprocessing (normalization, sequence padding), models can show erratic outputs during high volatility, affecting prediction stability

Dataset Limitations

- Training on historical data from a single company or limited period restricts generalization across other stocks or market conditions.
- Publicly available daily data omit intraday patterns, trading volumes, and order book dynamics, limiting temporal resolution and responsiveness

Model Interpretability

- Training on historical data from a single company or limited period restricts generalization across other stocks or market conditions.
- Publicly available daily data omit intraday patterns, trading volumes, and order book dynamics, limiting temporal resolution and responsiveness

Computational Constraints

- Real-time inference requires considerable computational resources, particularly on devices without GPU support.
- Large-scale deployment or multi-asset prediction increases infrastructure complexity and cost due to the need for parallel processing or cloud GPU acceleration.

Market Event Blindness

- Sequential models rely solely on historical price data and do not account for upcoming events such as earnings reports or geopolitical news.
- This can lead to predictions that lag behind real market shifts.

VIII. FUTURE SCOPE

The future scope of stock price prediction using LSTM and GRU models lies in enhancing their predictive accuracy, efficiency, and practical applicability. Integrating real-time news sentiment and social media trends as auxiliary inputs can help both models anticipate market-moving events driven by investor emotions and behavioral factors. Advanced architectures, such as transformers or hybrid LSTM-GRU models, can capture longer dependencies and complex temporal patterns, while GRU's computational efficiency makes it suitable for real-time and mobile deployments.

Expanding to multivariate forecasting allows simultaneous prediction across multiple assets, supporting portfolio optimization and risk assessment. Additionally, incorporating alternative data sources like satellite imagery, traffic, or macroeconomic indicators can strengthen prediction robustness. Employing AutoML frameworks for automated hyperparameter tuning, along with Explainable AI techniques like SHAP or LIME, can improve model transparency, interpretability, and regulatory compliance. Together, these enhancements position LSTM and GRU models as versatile tools for adaptive, real-time financial forecasting, capable of supporting both individual and institutional investment decisions.

Real-Time Deployment with AutoML

To make the prediction system production-ready, it must support real-time inference with robust handling of incoming data, missing values, and anomalies. AutoML frameworks such as Google Cloud AutoML or H2O.ai can automate hyperparameter tuning, feature engineering, and model selection, resulting in performance gains with reduced human effort. A live prediction dashboard built using Streamlit or Plotly Dash, integrated with financial APIs like Alpha Vantage or Yahoo Finance, can provide accessible and user-friendly forecasting tools to traders, investors, and researchers.

Mobile and Edge Device Adaptation

Expanding the system to mobile platforms through lightweight frameworks like TensorFlow Lite or ONNX could allow on-the-go forecasting for individual investors. With model compression and quantization, stock prediction could run even on resource-constrained edge devices. This paves the way for financial mobile apps that offer adaptive, real- time market insights, especially in emerging markets where desktop access may be limited.

IX. CONCLUSION

The proposed system for stock price prediction using LSTM marks a substantial step forward in leveraging deep learning for financial time series forecasting. By utilizing the Long Short-Term Memory (LSTM) neural network architecture, this project demonstrates the capacity of modern AI to capture complex temporal dependencies and nonlinear trends within stock market data—something that traditional statistical models often fail to represent adequately. At the core of the system lies a well-trained LSTM model, developed and fine-tuned using historical stock data to predict future closing prices with reasonable accuracy.

The model structure was carefully chosen to preserve temporal context and mitigate issues such as vanishing gradients. With validation metrics like MSE and RMSE, the system proved effective in modeling price trajectories across multiple epochs, ensuring a balance between underfitting and overfitting. Real-time predictions are supported through a streamlined Google Colab interface, showcasing the model's practical usability even outside high-end computational environments.

The integration of LSTM and GRU models for stock price prediction, combined with news and sentiment analysis, provides a comprehensive approach to understanding and forecasting market movements. LSTM effectively captures long-term dependencies in historical stock data, while GRU offers faster computation and efficient handling of short- term fluctuations. Incorporating sentiment from financial news and social media enhances predictive accuracy by reflecting the market's emotional and behavioral influences. Comparative analysis shows that both models perform well, with LSTM slightly better for long-term trends and GRU excelling in speed. This hybrid approach demonstrates the potential of combining numerical and textual data, making it a robust and practical tool for informed investment decisions and future enhancements in stock market forecasting.

Furthermore, evaluations in terms of accuracy, scalability, and responsiveness have been critical in positioning the model as a reliable foundation for more robust financial analytics systems. In a broader context, this work highlights the transformative potential of deep learning in stock market prediction. Comparative analysis shows that LSTM achieved slightly higher accuracy in capturing overall trends, whereas GRU performed comparably with faster training time. This demonstrates that both models, when combined with sentiment analysis, can significantly improve forecasting accuracy and reliability for informed investment decisions.

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