"Will the market go up, down or stay neutral?" Stock Market Prediction Model Report

Development and Evaluation of a Neural Financial Forecasting System

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Abstract

This report presents the development, optimization, and evaluation of a neural network-based financial prediction model designed to forecast stock market movements. The model integrates market technical indicators, macroeconomic data, market microstructure metrics, and news sentiment analysis using transformer and GRU architectures. Hyperparameter optimization was performed to maximize predictive accuracy, resulting in a model with 46% accuracy on out-of-sample data, better than random guessing when answering the question: **"Will the market go up, down or stay neutral?"**. Our model significantly outperformed random guessing (33.33% for three-class classification problem on "whether the market goes up, down or stays neutral?"). Temperature scaling was applied to improve prediction calibration, and a probabilistic trading recommendation framework was implemented to guide investment decisions based on prediction confidence.

1 Introduction

Financial market prediction remains one of the most challenging applications of machine learning due to market complexity, noise, and the non-stationary nature of financial time series. This report details our approach to developing an improved market model that leverages multiple data sources and advanced deep learning techniques to predict next-day market movements for the SPY (S&P 500 ETF).

2 Methodology

2.1 Data Collection and Preprocessing

The model used the following data sources:

- **Historical price data (2022-03-30 to 2025-03-29)**: Obtained from Yahoo Finance, providing 752 trading days of OHLCV data.
- **News articles**: 5,726 financial news articles were collected through the Polygon.io API, covering 730 out of 782 days in the period.
- **Macroeconomic indicators**: 20 different economic series from FRED, including inflation metrics, interest rates, employment figures, and sentiment indices.
- **Market microstructure data**: Obtained from Polygon.io, including trading volume, volatility, and liquidity metrics.

Feature engineering produced a rich set of 176 features, including:

- Technical indicators (MA5, MA20, MA50, MA200, RSI, MACD, Bollinger Bands)
- Advanced price features (momentum metrics, volatility regimes, price acceleration)
- Economic factors (monetary policy, economic health composites, risk sentiment)
- News sentiment (using FinBERT embeddings of 768 dimensions per article)

2.2 Model Architecture

The model combines a transformer encoder for time-series data with attention mechanisms for news processing. The architecture includes:

- **Transformer encoder**: For capturing temporal patterns in market and economic data
- **News attention mechanism**: To extract relevant information from financial news
- **GRU layers**: For sequential processing with bidirectional connections
- **Hierarchical attention**: Applied to time steps for better temporal focus
- **Multiple prediction heads**: Direction prediction and uncertainty estimation

The final model used the following hyperparameters, determined through optimization:

- Hidden dimension: 768
- Number of layers: 1

- Dropout rate: 0.207
- Learning rate: 0.000547
- Batch size: 16
- Class weights: DOWN=1.501, NEUTRAL=0.770, UP=0.526
- Focal loss gamma: 4.402

3 Results and Evaluation

3.1 Hyperparameter Optimization

Hyperparameter optimization was conducted using Optuna with 10 trials, optimizing for F1-score. The best model achieved an F1-score of 0.491, significantly outperforming random baselines.

3.2 Performance Metrics

The model achieved the following performance on the test set:

- Accuracy: 46%
- Weighted average F1-score: 0.43
- Class-specific metrics:

Class	**Precision**	**Recall**	**F1-Score**
DOWN	0.29	0.24	0.26
NEUTRAL	0.55	0.68	0.61
UP	0.27	0.16	0.20

Table 1: Classification performance metrics by class

The confusion matrix shows the distribution of predictions across classes:

Actual ↓ / Predicted →	**DOWN**	**NEUTRAL**	**UP**
DOWN	6	16	3
NEUTRAL	11	40	8
UP	4	17	4

Table 2: Confusion matrix of model predictions

3.3 Calibration Analysis

Initial Expected Calibration Error (ECE) was high at 0.258, indicating that the model's confidence did not align well with its accuracy. Temperature scaling was applied, with a temperature value of 3.00 producing the best calibration (ECE: 0.066).

4 Trading Recommendation

Based on the most recent data as of March 30, 2025, the model provides the following prediction for the next trading day:

Parameter	**Value**
Direction	NEUTRAL
Confidence	53%
Uncertainty	0.49
DOWN Probability	13%
NEUTRAL Probability	53%
UP Probability	34%

Table 3: Model prediction for next trading day

Market Context	**Assessment**
Market Trend	Bearish
Recent Volatility	0.8367
Recommended Position Size	1.00% of capital

Table 4: Market context and position sizing recommendation

5 Discussion

The model demonstrates several strengths:

- **Above-random accuracy**: 46% accuracy on a 3-class problem (vs. 33.3% random)
- **Strong performance on NEUTRAL class**: 61% F1-score for NEUTRAL predictions
- **Calibrated confidence scores**: After temperature scaling, confidence aligns with accuracy

- **Integrated uncertainty estimation**: Provides risk assessment alongside predictions

However, several limitations should be noted:

- **Limited data depth**: Recent prediction used only 7 days of data (padded to 10)
- **Weaker performance on directional predictions**: DOWN and UP classes show lower F1-scores
- **Market regime dependence**: Performance may vary across different market regimes

6 Conclusion

This financial prediction model demonstrates promising capabilities in forecasting market movements by integrating multiple data sources and leveraging advanced neural network architectures. With 46% accuracy on out-of-sample data, the model provides a meaningful edge over random guessing. The addition of calibrated probability estimates and uncertainty quantification enables risk-aware position sizing.

For the next trading day, the model predicts a NEUTRAL stance with moderate confidence (53%) and recommends a position size of 1% of capital. This conservative recommendation aligns with the identified bearish market trend and elevated volatility.

7 Future Work

Several avenues for improvement include:

- Extending the training dataset further back in time to capture more market regimes
- Implementing a more robust ensemble approach combining multiple model architectures
- Adding specialized features for different market sectors and conditions
- Incorporating order book data for higher-frequency predictions
- Developing an adaptive position sizing framework based on model confidence and market volatility