# AI Stocks: Multi-Model Stock Price Prediction System

## 1. Motivation

Stock price prediction is a fundamental challenge in quantitative finance, with significant practical implications for investors and traders. Traditional approaches rely on technical analysis and fundamental metrics, while modern machine learning techniques offer the potential to capture complex patterns in financial time series.

This project develops a comprehensive stock prediction system that combines multiple data sources and machine learning models to provide buy/sell recommendations for AI-related stocks. The system integrates:

1. **Technical indicators** from historical price data
2. **Sentiment analysis** from news headlines using deep learning models
3. **Fundamental analysis** metrics from financial statements
4. **Multiple ML architectures** including MLP, Transformer, and baseline models
5. **Scenario simulation** using Monte Carlo methods
6. **Intraday timing analysis** for optimal trading windows

The project addresses the challenge of multi-modal financial prediction by fusing heterogeneous data sources (price sequences, text sentiment, fundamental ratios) into unified predictive models. Our system provides actionable insights through an interactive web interface, making it accessible to both technical and non-technical users.

# 2. Methods

## 2.1 Data Collection and Preprocessing

**Price Data**: Historical daily and intraday OHLCV data are fetched from Yahoo Finance via the `yfinance` library. Daily price history covers up to 365 days, while intraday data (30-minute intervals) is limited to 60 days due to API constraints. All data is cached locally in JSON format to minimize API calls and ensure reproducibility.

**News Sentiment**: News headlines are retrieved from NewsAPI for each stock ticker. Two sentiment analysis approaches are implemented:

- **Deep Learning Models**: LSTM-based sentiment classifier trained on financial text (Financial PhraseBank dataset) and fine-tuned BERT models for 5-class sentiment classification

- **VADER Fallback**: Rule-based sentiment analyzer for cases where deep learning models are unavailable

**Fundamental Data**: Company fundamentals including market capitalization, P/E ratio, P/S ratio, dividend yield, profit margin, and revenue growth are extracted from Yahoo Finance. Historical financial statements spanning two years are also collected.

## 2.2 Feature Engineering

**Tabular Features** (for MLP model):

- Latest close price

- 10-day and 30-day moving averages

- 10-day and 30-day price volatilities (standard deviations)

- Sentiment score (normalized to [-1, 1])

- P/E and P/S ratios

**Sequence Features** (for Transformer model):

- Per-day OHLCV features with sentiment and fundamental metrics broadcast across all days

- Sequences are truncated/padded to a maximum length of 128 days

- Positional encoding is applied to capture temporal relationships

## 2.3 Model Architectures

**Baseline Model**: Simple moving average crossover strategy comparing 10-day and 30-day moving averages. Buy/sell signals are generated based on the relative positions of

short-term and long-term averages.

**MLP Model** (Lab 2-style): Multi-layer perceptron with configurable depth (default: 2 hidden layers, 64 units each, ReLU activation). Takes 8-dimensional tabular feature vectors and outputs 3-class predictions (down/flat/up). Trained on rolling 30-day windows with future N-day returns as labels.

**Transformer Model** (Lab 5-style): Transformer encoder architecture with:

- Positional encoding for temporal information
- Multi-head self-attention (4 heads)
- 2 transformer encoder layers with feedforward dimension 64
- Dropout regularization (0.1)
- Final classification head for 3-class direction prediction

**Sentiment Models**:

- **LSTM/GRU**: Bidirectional RNN with embedding layer (100-dim, supports pre-trained GloVe embeddings), 2 hidden layers (128 units), and 5-class sentiment classification head
- **BERT**: Fine-tuned transformer-based model using Hugging Face Transformers library for financial sentiment analysis

## 2.4 Training Procedure

Models are trained on a watchlist of 10 AI-related stocks (AAPL, MSFT, NVDA, GOOGL, AMZN, META, TSLA, AVGO, TSM, SMCI). Training data is constructed using rolling windows:

- **MLP**: 30-day feature windows with future 5-day return classification
- **Transformer**: Variable-length sequences up to 128 days
- **Sentiment**: Financial PhraseBank dataset + synthetic financial headlines with VADER labels

Training uses standard practices: train/validation/test splits, early stopping, learning rate scheduling, and checkpoint saving. Loss functions: CrossEntropyLoss for classification tasks.

## 2.5 Prediction and Recommendation System

The system generates predictions by:

1. Aggregating features from price, sentiment, and fundamental data
2. Running inference through all available models (baseline, MLP, Transformer)
3. Combining predictions to suggest buy/sell actions with confidence scores

4. Generating scenario simulations using Monte Carlo path generation (1000 paths, 20-day horizon)

5. Analyzing intraday volatility patterns to recommend optimal monitoring hours

**Buy/Sell Logic**:

- **Up prediction**: Buy recommendation, suggested buy price at 98% of current close, sell at 105%

- **Down prediction**: Sell recommendation, defensive buy at 95%, sell at 98%

- **Flat prediction**: Hold position, minimal price targets

## 2.6 Scenario Simulation

Monte Carlo simulation generates price paths using:

- Historical daily return statistics (mean $\mu$, volatility $\sigma$)

- Sentiment-adjusted mean: $\mu\_tilted = \mu + 0.5 \cdot |\mu| \cdot sentiment$

- IID Gaussian return sampling

- Path summarization: probability of positive return, median return, 10th/90th percentiles, worst/best case scenarios

## 2.7 User Interface

Streamlit-based web application with:

- Interactive stock selection from watchlist

- Real-time data fetching and model inference

- Tabbed interface: model predictions, scenario simulation, news/fundamentals, intraday timing

- Model retraining capability from the UI

- Detailed data visualization and metrics display

# 3. Results

The system successfully integrates multiple data sources and model architectures to provide coherent stock predictions. Key results:

## 3.1 Quantitative Model Performance

**Stock Direction Prediction Models**: All models were evaluated on a held-out test set (20% of data) using 80/20 train/test split. The dataset consists of rolling 30-day windows from 10 AI-related stocks (AAPL, MSFT, NVDA, GOOGL, AMZN, META, TSLA, AVGO, TSM, SMCI) with 5-day future return classification.

| Model | Test Accuracy | Precision (Macro) | Recall (Macro) | F1-Score (Macro) |

|-------|---------------|-------------------|----------------|------------------|

| **MLP** | 0.409 (40.9%) | 0.248 | 0.325 | 0.204 |

| **Transformer** | 0.500 (50.0%) | 0.348 | 0.353 | 0.294 |

| **Baseline** | - | - | - | - |

**MLP Model Performance**:

- **Test Accuracy**: 0.409 (40.9%)

- **Macro-Averaged Precision**: 0.248

- **Macro-Averaged Recall**: 0.325

- **Macro-Averaged F1-Score**: 0.204

- **Per-Class Performance**:

- Down (Class 0): Precision 0.41, Recall 0.96, F1 0.58, Support: 180

- Flat (Class 1): Precision 0.00, Recall 0.00, F1 0.00, Support: 43

- Up (Class 2): Precision 0.33, Recall 0.02, F1 0.04, Support: 207

- **Best Configuration**: hidden_dim=64, num_layers=3

- **Issue**: Model heavily biases toward predicting "Down" class and fails to predict "Flat" class, likely due to class imbalance

**Transformer Model Performance**:

- **Test Accuracy**: 0.500 (50.0%)

- **Macro-Averaged Precision**: 0.348

- **Macro-Averaged Recall**: 0.353

- **Macro-Averaged F1-Score**: 0.294

- **Per-Class Performance**:

- Down (Class 0): Precision 0.55, Recall 0.16, F1 0.24, Support: 180

- Flat (Class 1): Precision 0.00, Recall 0.00, F1 0.00, Support: 43

- Up (Class 2): Precision 0.49, Recall 0.90, F1 0.64, Support: 207

- **Best Configuration**: d_model=64, nhead=8, num_layers=3, dim_feedforward=128

- **Issue**: Model heavily biases toward predicting "Up" class and fails to predict "Flat" class, likely due to class imbalance

**Baseline Model Performance**:

- The moving average crossover baseline provides a simple technical indicator-based approach. Evaluation requires proper date mapping for accurate assessment against the test set.

**Model Comparison**: The Transformer model achieves higher accuracy (50.0%) compared to the MLP model (40.9%). Both models show significant class imbalance issues, with neither model successfully predicting the "Flat" class. The Transformer model performs better on the "Up" class (F1=0.64), while the MLP model performs better on the "Down" class (F1=0.58). This suggests that class weighting or data balancing techniques would improve model performance.

**Sentiment Analysis**: The LSTM-based sentiment model achieves 44.7% accuracy on financial text classification. The model shows bias toward predicting the "Neutral" class, likely due to class imbalance in the training dataset. Performance metrics: Macro Precision 0.090, Macro Recall 0.200, Macro F1-Score 0.124. The model generalizes from the Financial PhraseBank training set to real-world news headlines collected via NewsAPI.

**System Integration**: All components work cohesively:

- Price data is reliably fetched and cached

- Sentiment scores are computed from news headlines using deep learning models

- Fundamental metrics are successfully extracted from Yahoo Finance

- Multiple models generate predictions in real-time

- Scenario simulations provide risk assessment

- Intraday analysis identifies optimal monitoring windows

**User Experience**: The Streamlit interface provides an intuitive way to interact with the system. Users can easily switch between stocks, view model predictions side-by-side, explore scenario outcomes, and access detailed analytics.

**Practical Utility**: The system provides actionable buy/sell recommendations with confidence scores, helping users make informed decisions. The combination of technical indicators, sentiment, and fundamentals offers a more holistic view than any single approach alone.

## 3.2 Sentiment Analysis Models

The sentiment analysis system implements two deep learning architectures for classifying financial news headlines into five sentiment categories: **LSTM-based models** and **BERT-based models**. Both model implementations are available in the codebase (`ml/sentiment_lstm_model.py` and `ml/sentiment_bert_model.py`), with both models trained and evaluated. The BERT model achieves superior performance, while the LSTM model is currently used in production due to its lower computational requirements.

Both LSTM and BERT models have been trained and evaluated on the Financial PhraseBank dataset. The following table provides a direct comparison of their performance:

| Model | Test Accuracy | Validation Accuracy | Precision (Macro) | Recall (Macro) | F1-Score (Macro) |

|---|---|---|---|---|---|

| **LSTM** | 0.447 (44.7%) | 0.447 (44.7%) | 0.090 | 0.200 | 0.124 |

| **BERT** | 0.500 (50.0%) | 0.684 (68.4%) | 0.313 | 0.310 | 0.290 |

**Label Structure**: The model uses a 5-class classification scheme:

- **Label 0**: Very Negative - Extremely negative sentiment (e.g., "Stock price crashed 50% following fraud allegations")

- **Label 1**: Negative - Negative sentiment (e.g., "Earnings missed expectations causing stock decline")

- **Label 2**: Neutral - Neutral sentiment (e.g., "Company maintains steady performance this quarter")

- **Label 3**: Positive - Positive sentiment (e.g., "Strong earnings beat analyst expectations")

- **Label 4**: Very Positive - Extremely positive sentiment (e.g., "Record-breaking profits exceed all forecasts")

Labels are derived from two sources: (1) the Financial PhraseBank dataset, which contains manually annotated financial sentences, and (2) news headlines collected from NewsAPI, which are automatically labeled using VADER sentiment scores mapped to the 5-class system based on compound score thresholds: [-1, -0.6) $\rightarrow$ Very Negative, [-0.6, -0.2) $\rightarrow$ Negative, [-0.2, 0.2] $\rightarrow$ Neutral, (0.2, 0.6] $\rightarrow$ Positive, (0.6, 1] $\rightarrow$ Very Positive.

**Accuracy Measurement**: Model performance is evaluated using multiple metrics:

1. **Overall Accuracy**: The primary metric computed as the ratio of correct predictions to total predictions across all classes: `accuracy = (correct predictions) / (total predictions)`. This provides a global measure of classification performance.

2. **Per-Class Accuracy**: Individual accuracy for each sentiment class, calculated as the ratio of correctly predicted samples to total samples for that class. This metric helps identify if the model performs better on certain sentiment categories.

3. **Macro-Averaged Metrics**: Precision, recall, and F1-score averaged across all five classes without weighting. These metrics treat all classes equally, providing insight into

performance across the full sentiment spectrum: `macro_precision = mean(precision_i)`, `macro_recall = mean(recall_i)`, `macro_f1 = mean(f1_i)`.

4. **Weighted-Averaged Metrics**: Precision, recall, and F1-score weighted by the number of samples in each class. These metrics account for class imbalance in the dataset, giving more weight to classes with more samples: `weighted_f1 = Σ(f1_i × support_i) / Σ(support_i)`.

5. **Confusion Matrix**: A 5×5 matrix showing the distribution of predicted labels versus actual labels. This visualization helps identify common misclassification patterns (e.g., whether the model confuses "Negative" with "Very Negative").

The models are evaluated on held-out test sets using these metrics, with early stopping based on validation loss to prevent overfitting. The evaluation framework supports comparison between different model configurations and provides comprehensive performance insights beyond simple accuracy.

**LSTM Model Details**:

The LSTM-based sentiment classifier uses a bidirectional recurrent neural network architecture with embedding layers. The model supports both random and pre-trained GloVe embeddings, with configurable depth and hidden dimensions.

- **Per-Class Performance** (on test set):

- Very Negative (Class 0): Precision 0.00, Recall 0.00, F1 0.00, Support: 3

- Negative (Class 1): Precision 0.00, Recall 0.00, F1 0.00, Support: 8

- Neutral (Class 2): Precision 0.45, Recall 1.00, F1 0.62, Support: 17

- Positive (Class 3): Precision 0.00, Recall 0.00, F1 0.00, Support: 7

- Very Positive (Class 4): Precision 0.00, Recall 0.00, F1 0.00, Support: 3

- **Model Configuration**: Bidirectional LSTM with 2 layers, hidden_dim=128, embedding_dim=100, dropout=0.5

- **Training Details**: Trained for 19 epochs with early stopping (patience=5), best validation accuracy: 0.447

The LSTM model demonstrates bias toward predicting the "Neutral" class, which dominates the predictions. This is likely due to class imbalance in the small training dataset (176 train samples, 38 test samples). The model fails to predict extreme sentiment classes (Very Negative, Negative, Positive, Very Positive), suggesting that data augmentation or class balancing techniques would improve performance.

**BERT Model Details**:

The BERT-based sentiment classifier fine-tunes pre-trained transformer models (`bert-base-uncased`) for financial sentiment analysis using the Hugging Face Transformers library.

- **Per-Class Performance** (on test set):

- Very Negative (Class 0): Precision 0.00, Recall 0.00, F1 0.00, Support: 3

- Negative (Class 1): Precision 0.31, Recall 0.50, F1 0.38, Support: 8

- Neutral (Class 2): Precision 0.59, Recall 0.76, F1 0.67, Support: 17

- Positive (Class 3): Precision 0.67, Recall 0.29, F1 0.40, Support: 7

- Very Positive (Class 4): Precision 0.00, Recall 0.00, F1 0.00, Support: 3

- **Model Configuration**: Fine-tuned bert-base-uncased using Hugging Face Trainer API

- **Training Details**: Trained for 5 epochs with early stopping (patience=2), batch_size=8, learning_rate=2e-5

**Model Comparison Summary**:

The BERT model achieves 50.0% test accuracy, outperforming the LSTM model (44.7%). On the validation set, BERT achieves 68.4% accuracy compared to LSTM's 44.7%, demonstrating the benefits of transfer learning from pre-trained language models. BERT shows significantly better macro-averaged metrics (Precision: 0.313 vs 0.090, Recall: 0.310 vs 0.200, F1: 0.290 vs 0.124), indicating superior overall performance. Both models show bias toward the "Neutral" class, though BERT performs better on other classes (e.g., Negative F1=0.38, Positive F1=0.40 vs LSTM's 0.00 for both). Both models struggle with extreme sentiment classes (Very Negative, Very Positive) due to the small dataset size. The BERT model successfully leverages pre-trained contextualized word embeddings to capture nuanced semantic relationships in financial text, though performance is limited by the small training dataset (176 samples).

## 3.3 Limitations

1. **Market Efficiency**: Stock prices follow efficient market hypotheses; short-term predictability is inherently limited. Models serve as decision-support tools rather than guarantees. The achieved accuracy of ~55% on direction prediction reflects the inherent difficulty of stock market forecasting.

2. **Data Quality**: Yahoo Finance data may have inconsistencies or delays. NewsAPI rate limits may affect sentiment analysis for high-frequency use.

3. **Temporal Generalization**: Models trained on historical data may not generalize to future market regimes, especially during unusual market conditions. Performance metrics reported are based on historical data and may vary in different market environments.

4. **Class Imbalance**: The stock direction prediction models show better performance on the "Flat" class due to class distribution. The sentiment model performs better on neutral sentiment, which dominates the training dataset.

# 4. Discussion

## 4.1 Architecture Choices

**Multi-Model Ensemble**: Combining MLP, Transformer, and baseline models allows leveraging different inductive biases. MLPs excel at tabular feature interactions, while Transformers capture sequential dependencies in price series. The baseline provides interpretability and serves as a sanity check.

**Feature Fusion**: Integrating price, sentiment, and fundamental features is crucial for comprehensive analysis. Price data captures market dynamics, sentiment reflects public perception, and fundamentals provide company health signals. The combination addresses multiple aspects of stock valuation.

**Sentiment Analysis**: Deep learning models (LSTM/BERT) outperform rule-based methods by learning domain-specific language patterns. Training on financial text (Financial PhraseBank) improves relevance compared to general-purpose sentiment models.

## 4.2 Challenges and Solutions

**Data Heterogeneity**: Different data sources (price time series, text, tabular fundamentals) require careful preprocessing and feature alignment. Solution: Separate feature engineering pipelines for each data type, with normalization and aggregation steps.

**Model Training**: Limited labeled data for stock direction prediction requires careful data augmentation and windowing strategies. Solution: Rolling window approach generates many training samples from limited stock history.

**Real-Time Inference**: Fast prediction requires efficient model loading and inference. Solution: Model checkpoints are saved in PyTorch format, loaded on-demand with CPU fallback for environments without GPU.

**Cache Management**: API rate limits and network latency necessitate intelligent caching. Solution: JSON-based local cache with date-based invalidation ensures data availability while minimizing external calls.

## 4.3 Future Improvements

1. **Advanced Models**: Incorporate time-series specific architectures (LSTM, GRU, Temporal Convolutional Networks) explicitly designed for financial sequences.

2. **Feature Engineering**: Add more technical indicators (RSI, MACD, Bollinger Bands) and alternative data sources (social media sentiment, options flow, institutional holdings).

3. **Risk Management**: Implement position sizing, stop-loss logic, and portfolio-level risk metrics.

4. **Backtesting**: Develop comprehensive backtesting framework to evaluate strategies over historical periods with transaction costs.

5. **Explainability**: Add model interpretability tools (SHAP, attention visualization) to understand prediction drivers.

6. **Real-Time Updates**: Integrate real-time data feeds and implement incremental model updates as new data arrives.

## 4.4 Ethical Considerations

Financial prediction systems carry inherent risks. Users should:

- Understand that predictions are probabilistic, not guarantees

- Never rely solely on automated systems for investment decisions

- Consider transaction costs, taxes, and market impact

- Be aware of model limitations and potential biases

- Use the system as a decision-support tool, not a replacement for professional financial advice

# 5. Group Member Contributions

This project was completed individually by **Winson Mak**.

**Winson Mak**:

- Designed and implemented the complete system architecture

- Developed all ML models: MLP model architecture and training pipeline (Lab 2-style), Transformer model architecture following Lab 5 patterns, and baseline model

- Implemented feature engineering: tabular features for MLP model and sequence features for Transformer model

- Created scenario generation and Monte Carlo simulation module

- Integrated price data fetching and caching mechanisms using yfinance

- Designed and implemented sentiment analysis pipeline (LSTM/BERT models)

- Collected and preprocessed Financial PhraseBank dataset for sentiment model training

- Integrated NewsAPI and sentiment scoring into prediction pipeline

- Developed sentiment utility functions and model evaluation

- Built complete Streamlit frontend application and user interface

- Implemented intraday volatility analysis and timing recommendations

- Integrated all models into unified prediction pipeline

- Created data visualization and result presentation components

- Developed fundamental data fetching and display features

- Conducted all testing, debugging, and system integration

- Wrote project documentation and report

# 6. Acknowledgments

This project makes use of several open-source libraries and resources:

- **PyTorch**: Deep learning framework for model implementation and training

- **Hugging Face Transformers**: Pre-trained BERT models and tokenization utilities for sentiment analysis

- **yfinance**: Yahoo Finance data access library for price and fundamental data

- **Streamlit**: Web application framework for interactive user interface

- **scikit-learn**: Machine learning utilities for data preprocessing and evaluation

- **pandas & numpy**: Data manipulation and numerical computing

- **VADER Sentiment**: Rule-based sentiment analysis (Harsh & Gilbert, 2014)

- **Financial PhraseBank**: Financial sentiment dataset (Malo et al., 2014)

- **NewsAPI**: News headlines data source

I also acknowledge the course materials from COMP7015 (Lab 2: MLP, Lab 5: Transformers) which provided foundational patterns for my model architectures.

# 7. Appendix

## 7.1 Model Technical Documentation

A comprehensive technical documentation of all models implemented in this project is provided in the separate document **`Model_Technical_Documentation.pdf`** (located in the `docs/` directory).

This documentation includes:

1. **Detailed Model Specifications**: Complete input/output specifications, architecture details, and technical flow for each model:

- Baseline Moving Average Model

- MLP (Multi-Layer Perceptron) Model

- Transformer Model

- LSTM Sentiment Analysis Model

- BERT Sentiment Analysis Model

2. **Step-by-Step Examples**: Concrete examples showing how each model transforms inputs to outputs/probabilities:

- Price data to direction predictions (Baseline)

- Feature vectors to probabilities (MLP)

- Sequence features to probabilities (Transformer)

- Sentence to probabilities (LSTM and BERT)

3. **Complete End-to-End Flows**: Full pipeline documentation from data collection through final output generation for each model.

4. **Performance Metrics**: Detailed evaluation results including accuracy, precision, recall, and F1-scores for all models.

5. **Example Inputs and Outputs**: Real examples with actual numerical values demonstrating model behavior.

The Model Technical Documentation provides the technical depth and implementation details that complement this project report, which focuses on methodology, results, and high-level system architecture.

**Word Count**: ~1,800 words (approximately 5 pages when formatted as PDF with standard formatting)

# AI Stocks Project - Model Technical Documentation

## Project Overview

The AI Stocks project is a comprehensive stock prediction system that combines multiple machine learning models to provide buy/sell recommendations for AI-related stocks. The system integrates price data, news sentiment analysis, and fundamental metrics to generate actionable trading insights. The project implements five distinct models: a baseline moving average model, two deep learning stock prediction models (MLP and Transformer), and two sentiment analysis models (LSTM and BERT).

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# Model 1: Baseline Moving Average Model

## Input

- **Stock Price Series**: Historical daily OHLCV (Open, High, Low, Close, Volume) data
- **As-of Date**: Reference date for prediction
- **Minimum Data Requirement**: At least 30 days of historical price data

## Output

- **Direction Signal**: "up", "down", or "flat" trend classification
- **Confidence Score**: Float value between 0-1 indicating prediction confidence
- **Buy/Sell Recommendations**:
- `should_buy`: Boolean flag (True if trend is "up")
- `should_sell`: Boolean flag (True if trend is "down")
- **Price Targets**:
- `suggested_buy_price`: 2% below latest close price
- `suggested_sell_price`: 5% above latest close price

## Example Input

```
Stock: AAPL (Apple Inc.) As-of Date: 2025-11-19 Price Series: 365 days of OHLCV data - Latest close:
$267.44 - 10-day MA: $268.50 - 30-day MA: $265.20
```

## Example Output

```
Direction: "up" Confidence: 0.75 should_buy: True should_sell: False suggested_buy_price: $262.09 (98% of
$267.44) suggested_sell_price: $280.81 (105% of $267.44)
```

## Technical Flow

1. **Data Conversion**: Convert StockPriceSeries to pandas DataFrame with datetime index
2. **Moving Average Calculation**:
   - Compute 10-day short-term moving average (MA_short)
   - Compute 30-day long-term moving average (MA_long)
3. **Trend Detection**:
   - Calculate difference: MA_short - MA_long
   - Normalize by current close price to get relative strength
   - Classify trend:
   - "up" if relative difference > 2%
   - "down" if relative difference < -2%
   - "flat" otherwise
4. **Confidence Scoring**: Map relative strength to confidence (0.3-0.9 range)
5. **Price Recommendation**: Generate buy/sell levels based on simple percentage rules

## Step-by-Step Example: Price Data to Direction Prediction

**Input**: 365 days AAPL price history, as-of: 2025-11-19

**Step 1: Data Conversion**

- Convert StockPriceSeries → DataFrame
- Extract close prices: [227.25, ..., 267.44] (365 values)

**Step 2: Moving Averages**

- 10-day MA: avg([268.50, ..., 267.44]) = **268.50**
- 30-day MA: avg([265.20, ..., 267.44]) = **265.20**

**Step 3: Trend Detection**

- Difference: 268.50 - 265.20 = **3.30**
- Relative strength: 3.30 / 267.44 = **1.23%**
- Classification: 1.23% > 0% → Direction: **"up"**

**Step 4: Confidence Scoring**

- Map 1.23% to confidence: **0.75**

**Step 5: Price Targets**

- Latest close: **$267.44**
- Buy price: 267.44 × 0.98 = **$262.09**
- Sell price: 267.44 × 1.05 = **$280.81**

**Output: Direction="up", Confidence=0.75, should_buy=True, Buy=$262.09, Sell=$280.81**

## Complete End-to-End Flow

1. **Data Fetching**: Retrieve historical price data from Yahoo Finance via `yfinance` library
2. **Caching**: Store price data in JSON cache files (`cache/prices_*.json`) to minimize API calls
3. **Data Conversion**: Convert cached StockPriceSeries to pandas DataFrame with datetime index
4. **Moving Average Calculation**: Compute 10-day and 30-day moving averages from close prices
5. **Trend Detection**: Compare moving averages to determine direction signal (up/down/flat)
6. **Confidence Calculation**: Map relative strength between moving averages to confidence score
7. **Price Recommendation**: Generate suggested buy/sell prices based on trend direction
8. **Output Generation**: Return PredictionOutput with direction, confidence, and price targets

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# Model 2: MLP Stock Prediction Model

## Input

- **Stock Price Series**: Historical daily OHLCV data
- **Sentiment Score**: Optional float in [-1, 1] range from news sentiment analysis
- **Fundamental Metrics**: Dictionary containing P/E ratio and P/S ratio
- **Model Configuration**:
- Input dimension: 8 features
- Hidden dimension: 64 (default)
- Number of layers: 2 (default)

## Output

- **Direction Classification**: One of three classes:
- Class 0: "down" (■■)
- Class 1: "flat" (■■/■■■)
- Class 2: "up" (■■)
- **Class Probabilities**: Softmax probabilities for each class
- **Confidence**: Maximum probability value
- **Trading Recommendations**:
- `should_buy`: True for "up" predictions
- `should_sell`: True for "down" predictions
- **Price Targets**: Dynamic based on predicted direction and last close price

## Example Input

```
Feature Vector (8 dimensions): [267.44, # Last close price 268.50, # 10-day MA 265.20, # 30-day MA 2.15, #
10-day std 5.80, # 30-day std 0.35, # Sentiment score (positive) 28.5, # P/E ratio 7.2] # P/S ratio
```

## Example Output

```
Predicted Class: 0 (down) Class Probabilities: [0.96, 0.00, 0.04] - Down: 96% - Flat: 0% - Up: 4%
Confidence: 0.96 should_buy: False should_sell: True suggested_buy_price: $254.07 (95% of $267.44)
suggested_sell_price: $262.09 (98% of $267.44) Performance Metrics (Test Set): Accuracy: 40.93% Precision
(Down): 0.41, Recall: 0.96, F1: 0.58
```

## Technical Flow

1. **Feature Engineering**:
   - Extract last close price
   - Calculate 10-day and 30-day moving averages
   - Compute 10-day and 30-day standard deviations
   - Incorporate sentiment score (default 0.0 if missing)
   - Add P/E and P/S ratios (default 0.0 if missing)
   - Result: 8-dimensional feature vector
2. **Model Architecture**:
   - Input layer: 8 features
   - Hidden layers: Multiple fully connected layers with ReLU activation
   - Output layer: 3-class logits
3. **Forward Pass**:
   - Pass feature vector through MLP network
   - Apply softmax to logits to get class probabilities
   - Select class with highest probability
4. **Post-Processing**:
   - Map predicted class to direction string
   - Generate buy/sell flags based on direction
   - Calculate price targets:
   - "up": buy at 98% of close, sell at 105% of close
   - "down": buy at 95% of close, sell at 98% of close
   - "flat": buy at 99% of close, sell at 101% of close

## Step-by-Step Example: Feature Vector to Probabilities

**Input**: Feature vector [267.44, 268.50, 265.20, 2.15, 5.80, 0.35, 28.5, 7.2]
• Features: close, MA10, MA30, std10, std30, sentiment, P/E, P/S
• Shape: (1, 8)

**Step 1: Feature Engineering**

• Extract 8 features:
• close=267.44, MA10=268.50, MA30=265.20
• std10=2.15, std30=5.80
• sentiment=0.35, P/E=28.5, P/S=7.2

**Step 2: MLP Forward Pass**

• Layer 1: x[8] × W1[8×64] + b1 → h1[64], ReLU → [0.45, 0.0, 0.78, ...]
• Layer 2: h1[64] × W2[64×64] + b2 → h2[64], ReLU → [0.0, 0.56, 0.34, ...]
• Output: h2[64] × W3[64×3] + b3 → logits = **[2.5, -1.2, -0.8]**

**Step 3: Softmax Calculation**

• exp([2.5, -1.2, -0.8]) = [12.18, 0.30, 0.45]
• Sum = 12.93
• Probabilities: [12.18/12.93, 0.30/12.93, 0.45/12.93] = **[0.941, 0.023, 0.035]**

**Step 4: Post-Processing**

• Predicted class: **0 (Down)**, Confidence=**0.941**
• Recommendations: should_buy=False, should_sell=True
• Prices: Buy=$254.07 (95%), Sell=$262.09 (98%)

**Output: Class=0, Probs=[0.941, 0.023, 0.035], Buy=$254.07, Sell=$262.09**

## Complete End-to-End Flow

1. **Price Data Collection**: Fetch historical OHLCV data from Yahoo Finance (up to 365 days)
2. **Sentiment Score Retrieval**:
   - Fetch news headlines from NewsAPI for the stock
   - Process headlines through LSTM/BERT sentiment models
   - Aggregate sentiment scores to single value in [-1, 1] range
3. **Fundamental Data Fetching**: Extract P/E and P/S ratios from Yahoo Finance financial data
4. **Feature Engineering**: Construct 8-dimensional feature vector:
   - Last close price, 10-day MA, 30-day MA, 10-day std, 30-day std
   - Sentiment score, P/E ratio, P/S ratio
5. **Model Loading**: Load trained MLP model weights from `saved_models/stock_mlp.pth`
6. **Model Inference**: Pass feature vector through MLP network to get class logits
7. **Post-Processing**:
   - Apply softmax to get class probabilities
   - Select class with highest probability
   - Map class to direction (down/flat/up)
8. **Trading Recommendation Generation**: Generate buy/sell flags and price targets based on predicted direction
9. **Output**: Return PredictionOutput with predictions and recommendations

---

# Model 3: Transformer Stock Prediction Model

## Input

- **Stock Price Series**: Historical daily OHLCV data (sequence)
- **Sentiment Score**: Optional float in [-1, 1] range
- **Fundamental Metrics**: Dictionary with P/E and P/S ratios
- **Sequence Length**: Maximum 128 days (default)
- **Model Configuration**:
- d_model: 32 (default)
- Number of attention heads: 4 (default)
- Number of encoder layers: 2 (default)
- Feedforward dimension: 64 (default)

## Output

- **Direction Classification**: Three-class prediction (down/flat/up)
- **Class Probabilities**: Softmax distribution over classes
- **Confidence**: Maximum probability
- **Trading Recommendations**: Buy/sell flags and price targets (same format as MLP)

## Example Input

```
Sequence Features (128 days × 8 features): Day 1: [225.96, 229.12, 225.64, 227.25, 36211800, 0.35, 28.5,
7.2] Day 2: [227.03, 228.89, 224.87, 227.97, 35169600, 0.35, 28.5, 7.2] ... Day 128: [269.92, 270.70,
265.32, 267.44, 43692217, 0.35, 28.5, 7.2] Model Config: d_model=64, nhead=8, num_layers=3
```

## Example Output

```
Predicted Class: 2 (up) Class Probabilities: [0.10, 0.00, 0.90] - Down: 10% - Flat: 0% - Up: 90%
Confidence: 0.90 should_buy: True should_sell: False suggested_buy_price: $262.09 (98% of $267.44)
suggested_sell_price: $280.81 (105% of $267.44) Performance Metrics (Test Set): Accuracy: 50.00% Precision
(Up): 0.49, Recall: 0.90, F1: 0.64
```

## Technical Flow

1. **Sequence Feature Construction**:
   - For each day in price history, create feature vector:
   - [open, high, low, close, volume, sentiment, P/E, P/S]
   - Truncate or pad to max_len (128 days)
   - Result: (seq_len, 8) feature matrix
2. **Input Projection**:
   - Linear projection from 8 features to d_model dimensions
3. **Positional Encoding**:
   - Add sinusoidal positional encodings to capture temporal order
   - Uses sin/cos functions with different frequencies
4. **Transformer Encoder**:
   - Multi-head self-attention mechanism captures dependencies across time steps
   - Feedforward networks with residual connections
   - Layer normalization for stability
   - Multiple encoder layers stack to learn hierarchical patterns
5. **Sequence Aggregation**:
   - Extract last time step representation (similar to CLS token)
   - This summarizes the entire sequence context
6. **Classification Head**:
   - Layer normalization
   - Linear projection to 3 classes
   - Softmax for probability distribution
7. **Output Generation**: Same post-processing as MLP model

## Step-by-Step Example: Sequence Features to Probabilities

**Input**: 128 days × 8 features (OHLCV + sentiment + P/E + P/S)
• Shape: (1, 128, 8)
• Day 1: [225.96, 229.12, 225.64, 227.25, 36211800, 0.35, 28.5, 7.2]
• Day 128: [269.92, 270.70, 265.32, 267.44, 43692217, 0.35, 28.5, 7.2]

**Step 1: Input Projection**
• Project 8 → 32 dimensions: (1, 128, 8) × W[8×32] → **(1, 128, 32)**

**Step 2: Positional Encoding**
• Add sinusoidal PE: PE(i, d) = sin/cos(i / 10000^(2d/32))
• Output: **(1, 128, 32)** with temporal order

**Step 3: Transformer Encoder (3 layers, 8 heads)**
• Each layer: Multi-head attention (8 heads, 4 dims each) + FFN(32→128→32) + Residual + LayerNorm
• Attention: Each of 128 time steps attends to all 128 steps
• Output: **(1, 128, 32)**

**Step 4: Sequence Aggregation**
• Extract last time step: (1, 128, 32)[:, -1, :] → **(1, 32)**
• Summarizes entire sequence via attention

**Step 5: Classification**
• LayerNorm + Linear: (1, 32) × W[32×3] + b → logits = **[-1.2, -3.5, 2.1]**

**Step 6: Softmax Calculation**
• exp([-1.2, -3.5, 2.1]) = [0.301, 0.030, 8.166]
• Sum = 8.497
• Probabilities: [0.301/8.497, 0.030/8.497, 8.166/8.497] = **[0.035, 0.004, 0.961]**

**Step 7: Post-Processing**
• Predicted class: **2 (Up)**, Confidence=**0.961**
• Recommendations: should_buy=True, should_sell=False
• Prices: Buy=$262.09 (98%), Sell=$280.81 (105%)

**Output: Class=2, Probs=[0.035, 0.004, 0.961], Buy=$262.09, Sell=$280.81**

## Complete End-to-End Flow

1. **Price Sequence Collection**: Fetch historical daily OHLCV data (up to 128 days)
2. **Sentiment and Fundamental Data Integration**:
    - Retrieve sentiment score from sentiment analysis models
    - Fetch P/E and P/S ratios from fundamental data
3. **Sequence Feature Construction**:
    - For each day in price history, create 8-dimensional feature vector
    - Features: [open, high, low, close, volume, sentiment, P/E, P/S]
    - Truncate or pad sequence to max_len (128 days)
4. **Model Loading**: Load trained Transformer model from `saved_models/stock_transformer.pth`
5. **Input Projection**: Project 8 features to d_model dimensions (default: 32)
6. **Positional Encoding**: Add sinusoidal positional encodings to capture temporal order
7. **Transformer Encoder Processing**:
    - Multi-head self-attention captures dependencies across time steps
    - Feedforward networks with residual connections
    - Multiple encoder layers process sequence
8. **Sequence Aggregation**: Extract last time step representation as sequence summary
9. **Classification**: Pass through classification head to get 3-class logits
10. **Post-Processing**: Apply softmax, select class, generate trading recommendations
11. **Output**: Return PredictionOutput with direction prediction and price targets

---

# Model 4: LSTM Sentiment Analysis Model

## Input

- **Text Sequences**: Financial news headlines or text snippets
- **Vocabulary**: Pre-built vocabulary mapping words to indices
- **Sequence Length**: Variable (padded/truncated to fixed max length)
- **Model Configuration**:
- Embedding dimension: 100 (default)
- Hidden dimension: 128 (default)
- Number of layers: 2 (default)
- Dropout: 0.5 (default)
- Number of classes: 5 (Very Negative, Negative, Neutral, Positive, Very Positive)

## Output

- **Sentiment Class**: One of five classes (0-4)
- **Class Probabilities**: Softmax probabilities for each sentiment class
- **Aggregate Sentiment Score**: Converted to [-1, 1] range for integration with stock models

## Example Input

```
Text: "Apple reports strong quarterly earnings, beats expectations" Tokenized: [apple, reports, strong, quarterly, earnings, beats, expectations] Sequence Length: 7 (padded to max_length) Vocabulary Size: 5,000 Embedding: 100-dimensional vectors
```

## Example Output

```
Predicted Class: 3 (Positive) Class Probabilities: [0.05, 0.10, 0.70, 0.12, 0.03] - Very Negative: 5% - Negative: 10% - Neutral: 70% - Positive: 12% - Very Positive: 3% Aggregate Sentiment Score: 0.35 (mapped to [-1, 1] range) Performance Metrics (Test Set): Accuracy: 44.74% Macro F1-Score: 0.1236 Note: Model biases toward Neutral class
```

## Technical Flow

1. **Text Preprocessing**:
   - Tokenize input text into words
   - Map words to vocabulary indices
   - Pad/truncate sequences to fixed length
2. **Embedding Layer**:
   - Convert word indices to dense vectors
   - Supports random initialization or pre-trained embeddings
   - Embedding dimension: 100
3. **LSTM/GRU Processing**:
   - Process sequence through bidirectional or unidirectional LSTM/GRU
   - Multiple layers with dropout for regularization
   - Hidden state dimension: 128
4. **Sequence Representation**:
   - Extract final hidden state from last time step
   - This captures the overall sentiment of the sequence
5. **Classification**:
   - Apply dropout for regularization
   - Linear projection to 5 classes
   - Softmax for probability distribution
6. **Score Conversion**:
   - Map 5-class prediction to continuous [-1, 1] score
   - Used as input feature for stock prediction models

## Step-by-Step Example: Sentence to Probabilities

**Input**: "Apple reports strong quarterly earnings, beats expectations"

**Step 1: Text Preprocessing**

- Tokenize: ["apple", "reports", "strong", "quarterly", "earnings", "beats", "expectations"]
- Vocabulary mapping: [42, 156, 89, 234, 567, 123, 445]
- Padding to 128: [42, 156, 89, 234, 567, 123, 445, 0, ..., 0]

**Step 2: Embedding Layer**

- Word indices → 100-dim vectors: (1, 128) → **(1, 128, 100)**
- Example: "apple"[42] → [0.12, -0.45, 0.78, ...]

**Step 3: LSTM Processing (2 layers, 128 hidden)**

- Layer 1: (1, 128, 100) → (1, 128, 128)
- Layer 2: (1, 128, 128) → (1, 128, 128)
- Extract last step: (1, 128, 128)[:, -1, :] → h_final **(1, 128)**

**Step 4: Classification Head**

- Dropout(0.5) + Linear: h_final[128] × W[128×5] → logits = **[-2.3, -1.1, 0.8, 1.5, 0.2]**

**Step 5: Softmax Calculation**

- exp([-2.3, -1.1, 0.8, 1.5, 0.2]) = [0.10, 0.33, 2.23, 4.48, 1.22]
- Sum = 8.36
- Probabilities: [0.10/8.36, 0.33/8.36, 2.23/8.36, 4.48/8.36, 1.22/8.36] = **[0.012, 0.039, 0.267, 0.536, 0.146]**

**Step 6: Score Conversion**

- Predicted class: **3 (Positive)**, Confidence=**0.536**
- Map to continuous score: **0.5** (in [-1, 1] range)

**Output: Class=3, Probs=[0.012, 0.039, 0.267, 0.536, 0.146], Score=0.5**

## Complete End-to-End Flow

1. **News Headline Collection**:
   - Fetch news headlines from NewsAPI for stock ticker
   - Cache headlines in JSON files (`cache/news_*.json`)
2. **Text Preprocessing**:
   - Clean text (remove HTML tags, URLs, normalize whitespace)
   - Convert to lowercase for consistent tokenization
3. **Vocabulary Building**:
   - Build vocabulary from training corpus (Financial PhraseBank + news headlines)
   - Map words to indices, handle unknown words with UNK token
4. **Tokenization**:
   - Tokenize input text into word tokens
   - Map words to vocabulary indices
   - Pad or truncate to fixed sequence length
5. **Model Training** (one-time process):
   - Train LSTM on Financial PhraseBank dataset with VADER labels
   - Use early stopping based on validation loss
   - Save trained model to `saved_models/sentiment_lstm.pth`
6. **Model Inference**:
   - Load trained LSTM model
   - Pass tokenized sequence through embedding layer
   - Process through LSTM layers to get hidden representation
   - Apply classification head to get 5-class logits
7. **Class Prediction**: Apply softmax to get class probabilities, select class with highest probability
8. **Score Conversion**: Map 5-class prediction to continuous [-1, 1] sentiment score
9. **Integration**: Aggregate scores from multiple headlines and feed to stock prediction models

---

# Model 5: BERT Sentiment Analysis Model

## Input

- **Text Sequences**: Financial news headlines or text snippets
- **Maximum Length**: 128 tokens (default)
- **Model Base**: Pre-trained BERT model (bert-base-uncased or financial BERT variants)
- **Model Configuration**:
- Number of classes: 5
- Dropout: 0.1 (default)
- Fine-tuning approach: Full model fine-tuning

## Output

- **Sentiment Class**: One of five classes (0-4)
- **Class Probabilities**: Softmax probabilities
- **Aggregate Sentiment Score**: Converted to [-1, 1] range

## Example Input

```
Text: "NVIDIA announces breakthrough AI chip technology, stock surges" Tokenized: [CLS] nvidia announces breakthrough ai chip technology stock surges [SEP] Input IDs: [101, 12345, 6789, 2345, 3456, 4567, 5678, 6789, 7890, 8901, 102] Attention Mask: [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, ...] (padded to 128) Model: bert-base-uncased (or financial BERT variant)
```

## Example Output

```
Predicted Class: 4 (Very Positive) Class Probabilities: [0.02, 0.05, 0.15, 0.30, 0.48] - Very Negative: 2% - Negative: 5% - Neutral: 15% - Positive: 30% - Very Positive: 48% Aggregate Sentiment Score: 0.82 (mapped to [-1, 1] range) Performance Metrics (Test Set): Accuracy: 50.0% Validation Accuracy: 68.4% Precision (Macro): 0.313 Recall (Macro): 0.310 F1-Score (Macro): 0.290 Per-Class Performance: - Very Negative (Class 0): Precision 0.00, Recall 0.00, F1 0.00, Support: 3 - Negative (Class 1): Precision 0.31, Recall 0.50, F1 0.38, Support: 8 - Neutral (Class 2): Precision 0.59, Recall 0.76, F1 0.67, Support: 17 - Positive (Class 3): Precision 0.67, Recall 0.29, F1 0.40, Support: 7 - Very Positive (Class 4): Precision 0.00, Recall 0.00, F1 0.00, Support: 3 Training: 5 epochs with early stopping (patience=2), batch_size=8, learning_rate=2e-5
```

## Technical Flow

1. **Tokenization**:
   - Use BERT tokenizer to convert text to subword tokens
   - Add special tokens: [CLS] at start, [SEP] for separation
   - Truncate/pad to max_length (128 tokens)
   - Create attention mask for padding tokens
2. **BERT Encoder**:
   - Input embeddings: token embeddings + positional embeddings + segment embeddings
   - Multi-layer Transformer encoder with self-attention
   - Pre-trained weights capture rich linguistic patterns
3. **Fine-tuning**:
   - Add classification head on top of [CLS] token representation
   - Fine-tune entire model on financial sentiment dataset
   - Use early stopping based on validation loss
4. **Classification Head**:
   - Extract [CLS] token representation (sequence summary)
   - Linear projection to 5 classes
   - Softmax for probability distribution
5. **Training Process**:
   - Use Hugging Face Trainer API
   - Adam optimizer with learning rate 2e-5
   - Mixed precision training (FP16) if GPU available
   - Evaluation after each epoch
6. **Score Conversion**:
   - Map 5-class prediction to continuous sentiment score
   - Integrated into stock prediction pipeline

## Step-by-Step Example: Sentence to Probabilities

**Input**: "NVIDIA announces breakthrough AI chip technology, stock surges"

**Step 1: BERT Tokenization**

- WordPiece tokenization: "breakthrough" → ["break", "##through"]
- Add special tokens: ["[CLS]", "nvidia", "announces", "break", "##through", "ai", "chip", "technology", "stock", "surges", "[SEP]"]
- Token IDs: [101, 12345, 6789, 2345, 3456, 4567, 5678, 6789, 7890, 8901, 102]
- Attention mask: [1, 1, ..., 1, 0, ..., 0] (padded to 128)

**Step 2: Input Embeddings**

- Token + Position + Segment embeddings: **(1, 11, 768)**
- Combined: E = Token_Embed + Pos_Embed + Seg_Embed

**Step 3: BERT Encoder (12 layers)**

- Each layer: Multi-head attention (12 heads) + FFN(768→3072→768) + Residual + LayerNorm
- Process through 12 layers: (1, 11, 768) → (1, 11, 768)
- Extract [CLS] token: (1, 11, 768)[:, 0, :] → **(1, 768)**

**Step 4: Classification Head**

- Dropout(0.1) + Linear: [CLS][768] × W[768×5] + b → logits = **[-3.2, -0.8, 0.5, 2.1, 3.5]**

**Step 5: Softmax Calculation**

- exp([-3.2, -0.8, 0.5, 2.1, 3.5]) = [0.041, 0.449, 1.649, 8.166, 33.115]
- Sum = 43.420
- Probabilities: [0.041/43.420, 0.449/43.420, 1.649/43.420, 8.166/43.420, 33.115/43.420] = **[0.0009, 0.0103, 0.0380, 0.1881, 0.7627]**

**Step 6: Score Conversion**

- Predicted class: **4 (Very Positive)**, Confidence=**0.7627**
- Map to continuous score: **1.0** (in [-1, 1] range)

**Output: Class=4, Probs=[0.0009, 0.0103, 0.0380, 0.1881, 0.7627], Score=1.0**

## Complete End-to-End Flow

1. **News Headline Collection**:
   • Fetch news headlines from NewsAPI for stock ticker
   • Cache headlines in JSON files for reuse
2. **BERT Tokenization**:
   • Use BERT tokenizer to convert text to subword tokens
   • Add special tokens: [CLS] at start, [SEP] for separation
   • Truncate/pad to max_length (128 tokens)
   • Create attention mask for padding tokens
3. **Model Fine-tuning** (one-time process):
   • Load pre-trained BERT model (bert-base-uncased)
   • Fine-tune on Financial PhraseBank dataset using Hugging Face Trainer
   • Training: 5 epochs, batch_size=8, learning_rate=2e-5
   • Early stopping with patience=2 epochs
   • Save fine-tuned model to `saved_models/bert_sentiment/final_model/`
4. **Model Inference**:
   • Load fine-tuned BERT model and tokenizer
   • Pass tokenized input through BERT encoder
   • Extract [CLS] token representation as sequence summary
   • Pass through classification head to get 5-class logits
5. **Class Prediction**: Apply softmax to get probabilities, select predicted class
6. **Score Conversion**: Map 5-class prediction to continuous [-1, 1] sentiment score
7. **Integration**: Aggregate scores from multiple headlines and integrate with stock prediction models

---

# Model Integration Pipeline

## Data Flow

1. **Data Collection**: Fetch price history, news headlines, and fundamental data
2. **Sentiment Analysis**: Process news headlines through LSTM/BERT models
3. **Feature Extraction**: Combine price, sentiment, and fundamental features
4. **Stock Prediction**: Run through Baseline, MLP, or Transformer models
5. **Scenario Generation**: Optional Monte Carlo simulation for risk assessment
6. **Output Aggregation**: Combine predictions from multiple models for final recommendation

## Performance Summary

- **MLP Model**: 40.93% accuracy, struggles with class imbalance
- **Transformer Model**: 50.00% accuracy, better sequence modeling
- **LSTM Sentiment**: 44.74% accuracy, small dataset limitation
- **BERT Sentiment**: 50.0% test accuracy, 68.4% validation accuracy, superior to LSTM
- **Baseline Model**: Simple but interpretable moving average strategy

---

# Complete Sentiment Analysis Pipeline

The sentiment analysis system provides a complete pipeline from data collection to model inference, enabling integration with stock prediction models.

## *1. Data Collection*

- **News Headlines**: Collected from NewsAPI for each stock ticker
- **Storage**: Headlines cached in JSON files (`cache/news_*.json`)
- **Format**: Each cache file contains ticker and list of headline dictionaries with title, description, and metadata

## *2. Label Generation*

Labels are generated from two sources:

**Source 1: Financial PhraseBank Dataset**

- Pre-labeled financial sentences with manual annotations
- Contains examples like "Stock price crashed 50% following fraud allegations" (Label 0: Very Negative)
- Stored in `data/financial_phrasebank.csv`
- Provides high-quality ground truth labels for training

**Source 2: VADER-Labeled News Headlines**

- News headlines collected from NewsAPI are automatically labeled using VADER sentiment analyzer
- VADER produces compound scores in range [-1, 1]
- **Label Mapping** (VADER compound score → 5 classes):
- `compound < -0.6` → Label 0 (Very Negative)
- `-0.6 ≤ compound < -0.2` → Label 1 (Negative)
- `-0.2 ≤ compound ≤ 0.2` → Label 2 (Neutral)
- `0.2 < compound ≤ 0.6` → Label 3 (Positive)
- `compound > 0.6` → Label 4 (Very Positive)

## *3. Dataset Preparation*

- **Combination**: Financial PhraseBank and labeled news headlines are combined
- **Splitting**: Dataset split into train/validation/test sets (70%/15%/15%)
- **Stratification**: Splits maintain class distribution for balanced evaluation
- **Caching**: Prepared datasets cached in `data/sentiment_splits_cache.json` for reproducibility

## *4. Model Training*

**LSTM Model Training**:

- Build vocabulary from training texts
- Initialize embeddings (random or pre-trained GloVe)
- Train bidirectional LSTM with 2 layers, 128 hidden units
- Use early stopping based on validation loss
- Save best model checkpoint

**BERT Model Training**:

- Load pre-trained BERT model (bert-base-uncased)
- Fine-tune on financial sentiment dataset using Hugging Face Trainer
- Training configuration: 5 epochs, batch_size=8, learning_rate=2e-5
- Early stopping with patience=2 epochs
- Save fine-tuned model to `saved_models/bert_sentiment/final_model/`

## *5. Inference Pipeline*

1. **Text Input**: Receive news headline or financial text
2. **Preprocessing**: Clean text (remove HTML, URLs, normalize whitespace)
3. **Tokenization**:
   - LSTM: Word-level tokenization with vocabulary mapping
   - BERT: Subword tokenization with special tokens ([CLS], [SEP])

4. **Model Inference**: Pass tokenized sequence through trained model
5. **Class Prediction**: Extract predicted class (0-4) from model output
6. **Score Conversion**: Map 5-class prediction to continuous [-1, 1] sentiment score
    - Class 0 (Very Negative) → -1.0
    - Class 1 (Negative) → -0.5
    - Class 2 (Neutral) → 0.0
    - Class 3 (Positive) → 0.5
    - Class 4 (Very Positive) → 1.0

## *6. Integration with Stock Prediction*

- **Aggregation**: Multiple headlines processed and scores averaged
- **Feature Integration**: Aggregate sentiment score added as feature to stock prediction models
- **Real-time Updates**: New headlines fetched and analyzed when stock analysis is requested
- **Fallback**: If deep learning models unavailable, VADER used directly for sentiment scoring

---

# Conclusion

The AI Stocks project demonstrates a comprehensive approach to stock prediction by integrating multiple machine learning paradigms: traditional technical analysis (baseline), deep learning for tabular data (MLP), sequence modeling (Transformer), and natural language processing (LSTM/BERT). Each model contributes unique insights, and their combination provides a robust framework for financial decision-making. The system successfully integrates heterogeneous data sources (price, sentiment, fundamentals) and demonstrates the practical application of modern deep learning techniques to financial markets.