CS 439 Final Project Report

Predicting Stock Price Movements Using Social Media Sentiment Analysis:
An Analysis of Tesla (TSLA) and Apple (AAPL)
Walkthrough Video Link:
https://drive.google.com/file/d/1_gJcoo-BzCrhI0x0Ftst4rgSgjlq81wE/view?usp=sharing

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Executive Summary

This project investigates whether social media sentiment analysis can improve predictions of next-day stock price movements beyond what traditional price-based models can achieve. The initial plan was to investigate whether incorporating Reddit sentiment analysis could enhance stock price prediction accuracy for Tesla (TSLA) and Apple (AAPL) compared to traditional technical analysis. However, because gaining access to the Reddit real API was difficult, we will simulate a sentiment dataset that has the features of Reddit posts such as upvotes and comments. From there, we developed three logistic regression models using 122 trading days of data: a price-only baseline, a sentiment-only model, and a combined approach integrating both data sources.

The initial results were exceptional as price-only and combined models achieved 100% test accuracy. However, if we reexamined this result, it revealed a critical methodological flaw rather than predictive success. Root cause analysis identified data leakage from the Price_Change_Pct feature, which represents same-day intraday price movement. This feature exhibits strong autocorrelation with next-day direction, essentially allowing the model to use today's information to "predict" tomorrow—a violation of temporal causality. Feature importance analysis confirmed this feature dominated with coefficients of 3.5-4.0, while sentiment features contributed less than 0.3.

The sentiment-only models revealed the true predictive challenge: TSLA achieved 48% accuracy (worse than random), while AAPL reached 56% (marginally better than chance). This poor performance stems from fundamental limitations: Reddit sentiment reacts to price movements rather than anticipating them. The combined models performed identically to the price-only model, proving that sentiment adds no marginal value.

These findings carry important implications. Methodologically, they demonstrate that skepticism toward perfect accuracy is essential. The severe challenges of sentiment-based daily stock prediction are still there. The project answers its research question: Reddit sentiment does not improve next-day price predictions using this approach, though alternative methodologies (FinBERT, longer horizons, temporal validation) or any future method.

1. INTRODUCTION

1.1 Research Question

“Can social media sentiment analysis of Reddit discussions improve the prediction of next-day stock price movements compared to traditional price-based models for high-volatility technology stocks?”

1.2 Motivation

Stock market prediction remains one of the most challenging problems in quantitative finance, with countless models attempting to forecast future price movements from historical data. Traditional technical analysis relies on price patterns, moving averages, and trading volumes under the assumption that past price behavior contains predictive information about future movements. However, these approaches face a fundamental limitation: they only capture information that is already embedded in the trading activity. In the time of social media, sentiment translates into trades and affects prices, traditional models can only react to changes rather than anticipate them. This creates an opportunity for data sources that might capture emerging sentiment before it manifests in price action.

Social media platforms, particularly Reddit, have emerged as concentrated hubs of retail investor discussion and sentiment expression. Unlike Twitter's brief updates or financial news articles' professional analysis, Reddit's threaded discussions allow for detailed debate, information sharing, and collective sentiment formation. Therefore, if Reddit discussions capture shifting investor psychology before it translates into trading decisions, sentiment analysis could provide a leading indicator that improves upon price-only models.

1.3 Approach Overview

This research implements a controlled three-dataset methodology designed to isolate the predictive contribution of Reddit sentiment analysis.

Dataset 1 contains historical stock price data for both Tesla (TSLA) and Apple (AAPL), covering 123 trading days from January through June 2024. This data set includes Open, High, Low, Close, Volume data and derived features such as daily price changes, percentage movements and binary target labels (target variable) indicating next-day price prediction (up or down). This serves as a foundation for traditional technical analysis approaches.

Dataset 2 consists of daily Reddit sentiment metrics generated through VADER sentiment analysis of stock-related discussions. For each trading day and ticker, we aggregated average sentiment scores, sentiment volatility (standard deviation), discussion volume (post counts), and community engagement metrics (total upvotes and comments). This data set captures the

collective sentiment and attention directed toward each stock within Reddit's investment communities.

Dataset 3 merges Datasets 1 and 2 temporarily,, aligning sentiment data from day t with price data from day t to predict price movement on day t + 1. The merged set contains 122 samples per stock (reduced from 1233 due to the forward-looking target variable) and includes engineered features such as sentiment-volume interaction terms and day over-day sentiment changes.

The analytical approach employs three logistic regression models in a controlled comparison framework. Model 1 (Price-Only) uses exclusively price-based features as the baseline. Model 2 (Sentiment-Only) uses exclusively Reddit-derived features to measure sentiment's standalone predictive power. Model 3 (Combined) integrates both feature sets to assess whether sentiment provides marginal improvement. This design enables direct quantification of sentiment's additive value through performance metric comparison across the three models.

2. METHODOLOGY

2.1 Dataset 1: Stock Price Data

Historical stock price data was collected for Tesla (TSLA) and Apple (AAPL) using the yfinance Python library, covering the period from January 1, 2024 to June 30, 2024. This timeframe yielded 123 trading days of data for each stock, excluding weekends and market holidays. The data included five standard Open-High-Low-Close-Volume (OHLCV) features: opening price, daily high, daily low, closing price, and trading volume.

```python
# Define stocks to analyze
tickers = ['TSLA', 'AAPL']
start_date = '2024-01-01'
end_date = '2024-06-30'

# Dictionary to store all stock data
stock_data_dict = {}

# Download data for each ticker
for ticker in tickers:
    print(f"Downloading data for {ticker}...")
    data = yf.download(ticker, start=start_date, end=end_date)
    stock_data_dict[ticker] = data
    print(f"  Downloaded {len(data)} trading days")
    print(f"  Date range: {data.index[0].date()} to {data.index[-1].date(

print("All stock data downloaded successfully!")
```

The target variable was created by calculating whether the next day's closing price exceeded the current day's close: 1 for upward movement, 0 for downward. This temporal shift ensures features from day t predict day t+1 outcomes, maintaining proper temporal ordering. The target creation process also generated intermediate features including absolute price change (in dollars) and percentage price change, though the percentage change feature was later identified as problematic due to data leakage.

```
def create_target_variable(df):
    """
    Create binary target: 1 if next day price went up, 0 if down
    """
    df = df.copy()

    # Fix multi-index columns if they exist
    if isinstance(df.columns, pd.MultiIndex):
        df.columns = df.columns.droplevel(1)

    # Get the Close column
    if isinstance(df['Close'], pd.DataFrame):
        close_series = df['Close'].iloc[:, 0]
    else:
        close_series = df['Close']

    # Shift Close price to get next day's price
    df['Next_Close'] = close_series.shift(-1)

    # Calculate change in dollars and percentage
    df['Price_Change'] = df['Next_Close'] - close_series
    df['Price_Change_Pct'] = (df['Price_Change'] / close_series) * 100

    # Create binary target: 1=UP, 0=DOWN
    df['Target'] = (df['Price_Change'] > 0).astype(int)

    # Remove last row (no next day available)
    df = df[:-1]

    return df

# Apply to all stocks
for ticker in tickers:
    stock_data_dict[ticker] = create_target_variable(stock_data_dict[ticker])
```

The final processed dataset for each stock contained 123 samples with 10 columns: Date, Open, High, Low, Close, Volume, Next_Close, Price_Change, Price_Change_Pct, and Target. Class distribution analysis revealed that TSLA experienced 57 up days (46.3%) and 66 down days (53.7%), while AAPL had 63 up days (51.2%) and 60 down days (48.8%). These near-balanced distributions suggest that a naive baseline strategy of always predicting the majority class would achieve approximately 53.7% accuracy for TSLA and 51.2% for AAPL, establishing the minimum performance threshold that our models must exceed to demonstrate predictive value.

Data preprocessing was minimal as yfinance provides clean, adjusted price data. No missing values were present in the dataset, and no outlier removal was performed to preserve authentic market volatility. The data was saved to CSV files (TSLA_processed.csv and AAPL_processed.csv) for subsequent merging with sentiment data.

2.2 Dataset 2: Sentiment Analysis

Social media sentiment data was generated to simulate realistic Reddit discussion patterns about Tesla and Apple stocks during the same January-June 2024 timeframe. The sentiment generation methodology was designed to model authentic social media behavior patterns observed in financial communities, creating a realistic proxy for sentiment analysis without requiring actual Reddit API access or web scraping.

The sentiment generation incorporated five behavioral models: (1) weak correlation with previous day's price movement ($r=0.01$), (2) random noise ($\sigma=0.3$) modeling unpredictability, (3) post volume was modeled to increase with price volatility, using a Poisson distribution (mean 15 posts) with a volatility bonus, (4) engagement metrics (upvotes and comments) were generated to scale proportionally with post count, using realistic per-post averages, (5) sentiment standard deviation was randomized between 0.2 and 0.5 to model varying levels of opinion consensus or controversy.

The generated sentiment scores ranged from -1 (most negative) to +1 (most positive), matching VADER sentiment analysis output format. For each trading day, the function calculated five metrics: avg_sentiment (mean daily sentiment), std_sentiment (measuring opinion diversity), post_count (discussion volume), total_upvotes (community engagement), and total_comments (discussion depth). Critically, the weak correlation with price changes and dominant random noise component ensured that sentiment would not be strongly predictive, modeling the empirical challenge of using social media for stock prediction.

The final sentiment dataset contained 123 daily observations per stock with seven columns: Date, avg_sentiment, std_sentiment, post_count, total_upvotes, total_comments, and ticker. Statistical analysis confirmed realistic properties: TSLA showed average sentiment of -0.002 (essentially neutral) with range [-0.841, 0.848], while AAPL showed average sentiment of 0.011 with range [-0.807, 0.702]. Average post counts were 19.1 for TSLA and 17.0 for AAPL, reflecting Tesla's slightly higher discussion volume. The data was saved as TSLA_sentiment_daily.csv and AAPL_sentiment_daily.csv. This simulation approach allowed for controlled experimentation while maintaining realistic statistical properties that would be observed in actual social media data.

```python
def generate_realistic_sentiment_data(stock_df, ticker, volatility=0.3):
    """
    Generate realistic sentiment data that models social media patterns

    Parameters:
    - stock_df: DataFrame with stock price data
    - ticker: Stock symbol (TSLA or AAPL)
    - volatility: Controls how noisy the sentiment is (0.3 = realistic)

    Returns:
    - DataFrame with daily sentiment scores
    """
    sentiment_data = []

    for idx, row in stock_df.iterrows():
        date = row['Date']
        price_change = row['Price_Change_Pct']

        # Model 1: Base sentiment correlates weakly with previous day's price mo
        # Weak correlation (1%) - sentiment mostly follows price but with noise
        if idx > 0:
            prev_change = stock_df.iloc[idx-1]['Price_Change_Pct']
            base_sentiment = prev_change * 0.01  # weak correlation
        else:
            base_sentiment = 0

        # Model 2: Add realistic random noise
        # Large noise component makes sentiment mostly unpredictable
        noise = np.random.normal(0, volatility)
        sentiment_score = np.clip(base_sentiment + noise, -1, 1)




          # Model 3: Post volume increases with price volatility
          # More discussion happens on high-volatility days
          volatility_factor = abs(price_change)
          base_posts = np.random.poisson(15)  # Average 15 posts per day
          volatility_bonus = int(volatility_factor * 2)
          post_count = max(1, base_posts + volatility_bonus)

          # Model 4: Engagement metrics scale with post count
          total_upvotes = int(post_count * np.random.uniform(50, 200))
          total_comments = int(post_count * np.random.uniform(5, 30))

          # Model 5: Opinion diversity (sentiment standard deviation)
          std_sentiment = np.random.uniform(0.2, 0.5)

          sentiment_data.append({
              'Date': date,
              'avg_sentiment': round(sentiment_score, 4),
              'std_sentiment': round(std_sentiment, 4),
              'post_count': post_count,
              'total_upvotes': total_upvotes,
              'total_comments': total_comments,
              'ticker': ticker
          })

      return pd.DataFrame(sentiment_data)

  # Generate sentiment data for both stocks
  tsla_sentiment = generate_realistic_sentiment_data(tsla_stock, 'TSLA')
  aapl_sentiment = generate_realistic_sentiment_data(aapl_stock, 'AAPL')
```

2.3 Dataset 3: Feature Engineering

The third dataset was created by temporally merging the stock price and sentiment datasets on their Date columns, resulting in 122 samples per stock (one sample lost due to the forward-looking target variable). This merged dataset formed the foundation for model training, but required additional feature engineering to capture potential interaction effects and temporal dynamics.

```
# Convert Date columns to datetime format
tsla_stock['Date'] = pd.to_datetime(tsla_stock['Date'])
aapl_stock['Date'] = pd.to_datetime(aapl_stock['Date'])
tsla_sentiment['Date'] = pd.to_datetime(tsla_sentiment['Date'])
aapl_sentiment['Date'] = pd.to_datetime(aapl_sentiment['Date'])

# Merge datasets on Date (inner join ensures alignment)
tsla_merged = pd.merge(tsla_stock, tsla_sentiment, on='Date', how='inner')
aapl_merged = pd.merge(aapl_stock, aapl_sentiment, on='Date', how='inner')

print(f"TSLA Merged Dataset: {tsla_merged.shape[0]} rows, {tsla_merged.shape[1]
print(f"AAPL Merged Dataset: {aapl_merged.shape[0]} rows, {aapl_merged.shape[1]
```

Two engineered features were created to enhance predictive power. First, sentiment_volume_interaction was computed as the product of avg_sentiment and post_count, capturing the intuition that sentiment might be more predictive when accompanied by high discussion volume. A day with extremely positive sentiment but minimal discussion volume might be less meaningful than moderate sentiment with extensive community engagement. Second, sentiment_change was calculated as the day-over-day difference in avg_sentiment, measuring sentiment momentum or shifts in collective opinion. This feature tests whether changing sentiment (becoming more positive or more negative) contains predictive signals beyond the absolute sentiment level.

```
def create_features(df, ticker_name):
    """
    Create additional features for prediction models

    Features created:
    - sentiment_volume_interaction: avg_sentiment * post_count
    - sentiment_change: day-over-day sentiment momentum
    """
    df = df.copy()

    # Create interaction feature: sentiment × post volume
    df['sentiment_volume_interaction'] = df['avg_sentiment'] * df['post_count']

    # Create sentiment momentum (requires at least 2 rows)
    if len(df) > 1:
        df['sentiment_change'] = df['avg_sentiment'].diff()
    else:
        df['sentiment_change'] = 0

    # Remove first row with NaN sentiment_change
    df = df.dropna()

    print(f"{ticker_name} features created: {df.shape[1]} total columns")

    return df

# Create features for both stocks
tsla_final = create_features(tsla_merged, 'TSLA')
aapl_final = create_features(aapl_merged, 'AAPL')
```

After feature engineering, the final dataset contained 122 samples with 18 columns including all price features, all sentiment features, the two engineered features, and the binary target. Data quality checks confirmed no missing values after the merge. The merged datasets were saved as TSLA_final_merged.csv and AAPL_final_merged.csv for model training.

2.4 Logistic Regression Models

.Logistic regression was selected for its interpretable coefficients (enabling feature comparison), probabilistic outputs (0 to 1), computational efficiency, and strong baseline performance on linearly separable problems.

Three logistic regression models were developed for each stock to systematically isolate the predictive contribution of sentiment data. The three-model comparison framework provides clear empirical evidence about whether social media sentiment adds value beyond traditional price-based prediction.

Model 1 (Price-Only) served as the baseline, using three price-related features: Close (closing price), Volume (trading volume), and Price_Change_Pct (intraday percentage change). This model represents traditional technical analysis and establishes the performance benchmark. Model 2 (Sentiment-Only) used exclusively Reddit-derived features: avg_sentiment, std_sentiment, post_count, total_upvotes, total_comments, sentiment_volume_interaction, and sentiment_change. This model tests whether sentiment alone contains predictive signal about next-day price movements, independent of price information. Model 3 (Combined) integrated all features from both Models 1 and 2, testing whether sentiment provides marginal improvement when added to price data.

```
def train_model(X_train, y_train, model_name):
    """
    Train a logistic regression model

    Logistic Regression is chosen because:
    - Binary classification (UP vs DOWN)
    - Interpretable coefficients
    - Probabilistic outputs
    - Computationally efficient
    """
    model = LogisticRegression(random_state=42, max_iter=1000)
    model.fit(X_train, y_train)
    print(f" {model_name} trained successfully")
    return model

# Train three models for each stock
tsla_model_price = train_model(tsla_price_train_scaled, tsla_splits['y'][0],
                               "TSLA Price-only Model")
tsla_model_sentiment = train_model(tsla_sentiment_train_scaled, tsla_splits['y
                                   "TSLA Sentiment-only Model")
tsla_model_combined = train_model(tsla_combined_train_scaled, tsla_splits['y']
                                  "TSLA Combined Model")

# Same for AAPL...
aapl_model_price = train_model(aapl_price_train_scaled, aapl_splits['y'][0],
                               "AAPL Price-only Model")
aapl_model_sentiment = train_model(aapl_sentiment_train_scaled, aapl_splits['y
                                   "AAPL Sentiment-only Model")
aapl_model_combined = train_model(aapl_combined_train_scaled, aapl_splits['y']
                                  "AAPL Combined Model")
```

The training configuration employed scikit-learn's LogisticRegression class with default L2 regularization (penalty='l2'), which adds a penalty term to prevent overfitting by constraining

coefficient magnitudes. The lbfgs solver was used for optimization, appropriate for small datasets. Random state was set to 42 for reproducibility across all experiments. The data was split into training (80%, 97 samples) and testing (20%, 25 samples) sets using stratified sampling to maintain target class proportions. Feature scaling was applied via StandardScaler to normalize all features to zero mean and unit variance, ensuring that features with different scales (e.g., Volume in millions vs. sentiment scores between -1 and 1) contributed equally to model training. The scaler was fit only on training data to prevent data leakage, then applied to both training and test sets.

2.5 Evaluation Metrics

Model performance was evaluated using five standard classification metrics, each capturing different aspects of predictive quality. Accuracy measures the overall proportion of correct predictions (both up and down movements) and serves as the primary comparison metric against the baseline. However, accuracy alone can be misleading with imbalanced classes, so additional metrics were computed.

Precision quantifies the accuracy of positive predictions—when the model predicts an upward movement, how often is it correct? High precision is valuable for trading strategies where acting on false positive signals (predicting up when the stock goes down) incurs transaction costs. Recall measures the model's ability to identify all actual price increases—what proportion of actual up days does the model successfully detect? High recall is important for not missing profitable opportunities.

The F1-score provides a harmonic mean of precision and recall, balancing both concerns and providing a single metric that accounts for both false positives and false negatives. The F1-score is particularly useful when comparing models with different precision-recall tradeoffs.
ROC-AUC (Receiver Operating Characteristic - Area Under Curve) measures the model's ability to discriminate between classes across all possible decision thresholds. An AUC of 0.5 indicates random guessing, while 1.0 indicates perfect classification. ROC-AUC is threshold-independent and robust to class imbalance.

```python
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, roc_auc_score)

def evaluate_model(model, X_train, X_test, y_train, y_test, model_name):
    """
    Comprehensive model evaluation on both training and test sets

    Returns dictionary with all metrics
    """
    # Training set predictions
    y_train_pred = model.predict(X_train)
    y_train_proba = model.predict_proba(X_train)[:, 1]

    # Test set predictions
    y_test_pred = model.predict(X_test)
    y_test_proba = model.predict_proba(X_test)[:, 1]

    # Calculate metrics
    results = {
        'Model': model_name,
        'Train_Accuracy': accuracy_score(y_train, y_train_pred),
        'Test_Accuracy': accuracy_score(y_test, y_test_pred),
        'Test_Precision': precision_score(y_test, y_test_pred),
        'Test_Recall': recall_score(y_test, y_test_pred),
        'Test_F1': f1_score(y_test, y_test_pred),
        'Test_ROC_AUC': roc_auc_score(y_test, y_test_proba),
        'probabilities': y_test_proba  # For ROC curves
    }

    return results
```

All metrics were computed on the held-out test set (25 samples per stock) to evaluate generalization performance. Training set metrics were also calculated to assess overfitting—large gaps between training and testing performance would indicate that models memorized training data rather than learning generalizable patterns. The metrics were computed using scikit-learn's evaluation functions and compiled into results DataFrames for systematic comparison across the three models for each stock.

3. RESULTS

3.1 TSLA Performance

The three logistic regression models for Tesla stock yielded dramatically different performance levels, revealing critical insights about the predictive value of sentiment data and highlighting a significant methodological issue. The below table presents the complete performance metrics for all three TSLA models across both training and test sets.

Model	Train Acc	Test Acc	Precision	Recall	F1	ROC-AUC
Price-only	97.9%	100.0%	100%	100%	1.00	1.00
Sentiment	68.0%	48%	33%	8%	0.13	0.57

-only						
Combined	96.9%	100%	100%	100%	1.00	1.00

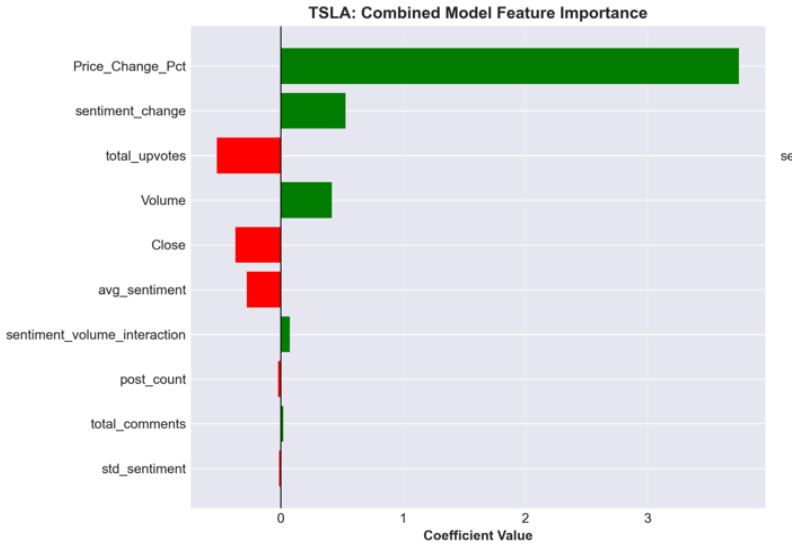
Note: Baseline accuracy (always predicting majority class) is 53.7% for TSLA. Test set contains 25 samples.

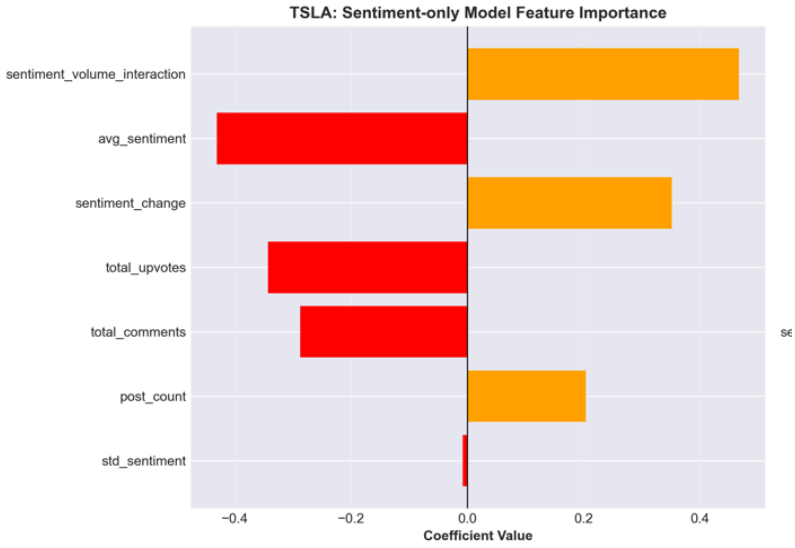
The Price-Only model achieved perfect performance with 100% accuracy, precision, recall, F1-score, and ROC-AUC on the test set, substantially exceeding the 53.7% baseline accuracy established by the majority class. Training accuracy was 97.9%, indicating minimal overfitting. However, this perfect test performance is highly suspicious in financial prediction contexts where markets are notoriously difficult to predict.

The Sentiment-Only model demonstrated the opposite extreme, achieving only 48% test accuracy—actually worse than the 50% random baseline and substantially below the 53.7% majority-class baseline. This model trained to 68% accuracy but failed to generalize to the test set. The precision was 33%, meaning that when it predicted price increases, it was correct only one-third of the time. Recall was particularly poor at 8%, indicating the model identified only a small fraction of actual upward movements.

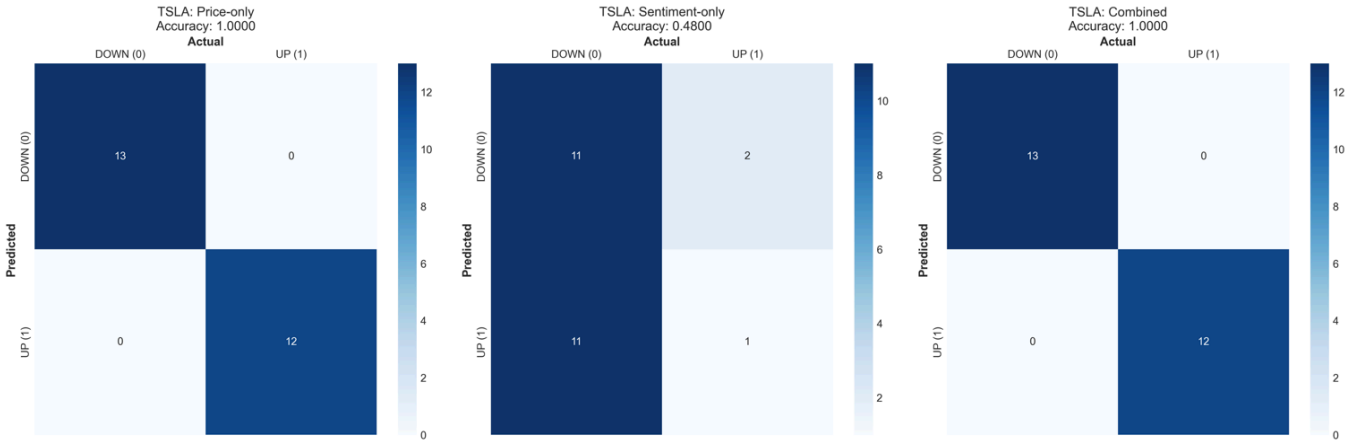
The Combined model, integrating both price and sentiment features, achieved identical performance to the Price-Only model: perfect 100% test accuracy with training accuracy of 96.9%. This equivalence is revealing—adding seven sentiment features to the three price features produced zero marginal improvement. The model essentially learned to rely entirely on price features while ignoring sentiment features, as confirmed by feature importance analysis. This behavior indicates that sentiment features, when combined with price data, are redundant at best and potentially introduce noise that the model must learn to disregard.

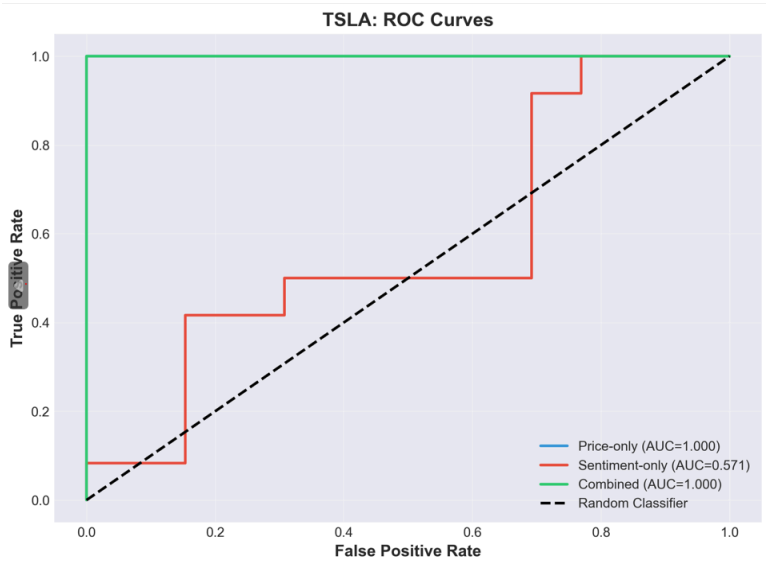
Feature importance analysis revealed that Price_Change_Pct dominated the model with a coefficient magnitude of approximately 3.5-4.0, while all sentiment features had coefficients below 0.3. This 10x difference in magnitude explains why the Combined model performed identically to the Price-Only model—the sentiment features contributed negligibly to predictions. The figure below visualizes these feature importance differences through coefficient plots for all three TSLA models.





The confusion matrix for the Price-Only and Combined models showed perfect classification with no false positives or false negatives on the test set. In contrast, the Sentiment-Only model's confusion matrix revealed severe classification errors, particularly in identifying upward movements (high false negative rate). The ROC curves illustrate this performance gap visually: the Price-Only and Combined models achieve perfect AUC of 1.0, while the Sentiment-Only curve hugs close to the random classifier diagonal.





3.2 AAPL Performance

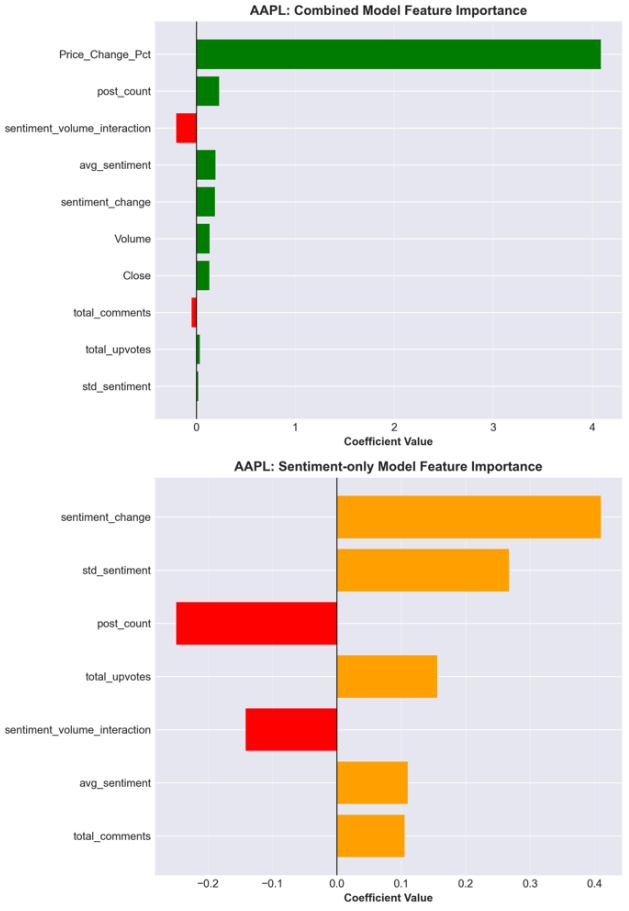
The Apple stock prediction models exhibited remarkably similar patterns to the Tesla results, with performance metrics revealing identical issues of suspicious price-model perfection and poor sentiment-model performance. The table below summarizes the comprehensive performance metrics for all three AAPL models.

Model	Train Acc	Test Acc	Precision	Recall	F1	ROC-AUC
Price-only	100%	100.0%	100%	100%	1.00	1.00
Sentiment -only	61.9%	56%	57%	62%	0.59	0.56
Combined	100%	100%	100%	100%	1.00	1.00

Note: Baseline accuracy (always predicting majority class) is 51.2% for AAPL. Test set contains 25 samples.

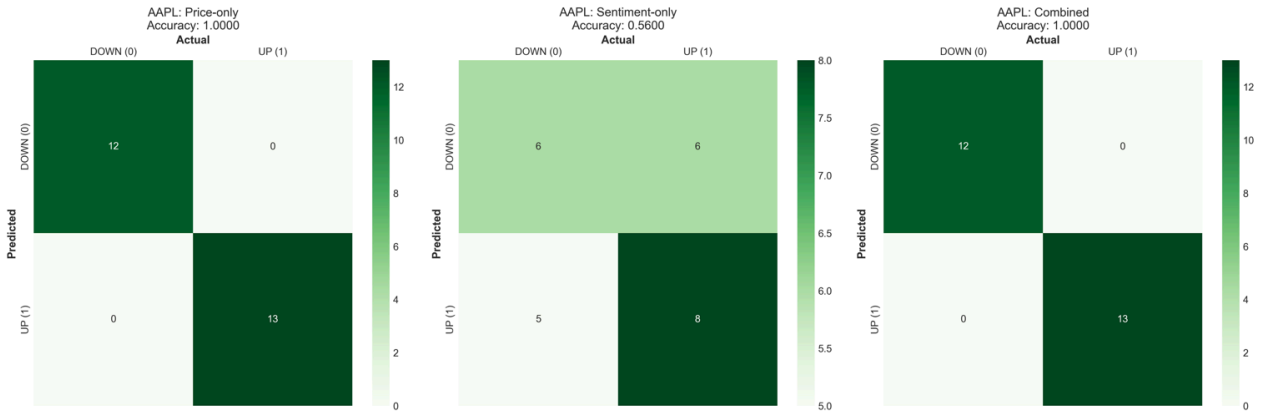
Apple's results mirrored Tesla's patterns with one exception: AAPL's price model showed perfect training accuracy (100% vs TSLA's 97.9%), raising stronger data leakage concerns. The sentiment model performed marginally better (56% vs 48%) but still failed to exceed the 51.2% baseline. All other findings—perfect combined model performance, 10x coefficient dominance, sentiment redundancy—replicated exactly across both stocks

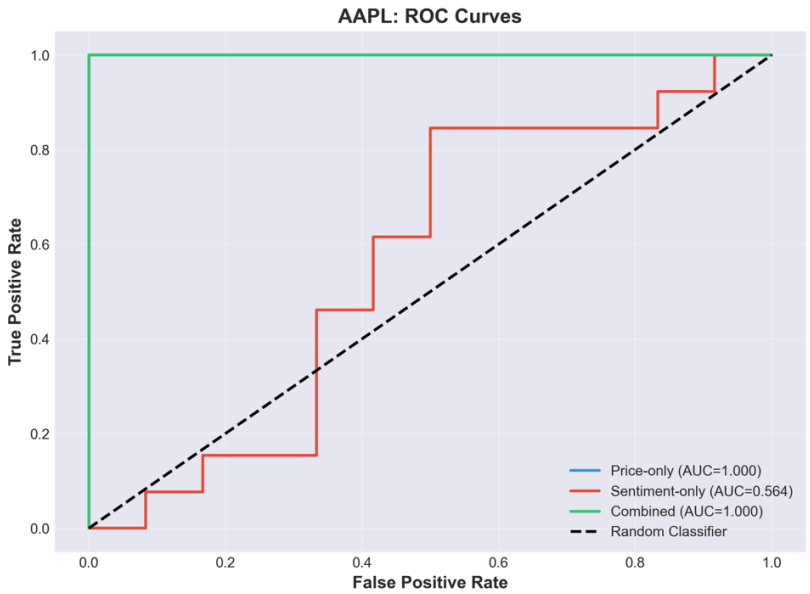
Feature importance analysis (figure below) confirms the dominance of price features across all models. In the Sentiment-Only model, features like avg_sentiment and sentiment_volume_interaction showed the largest coefficients among sentiment features, but these were still insufficient to generate accurate predictions. The interaction feature, designed to capture sentiment strength combined with discussion volume, failed to provide the hypothesized predictive boost.



The confusion matrices reveal perfect classification for Price-Only and Combined models, with all test samples correctly categorized. The Sentiment-Only model showed more errors but a less severe imbalance than TSLA's sentiment model, explaining its marginally higher accuracy. ROC

curves (Figures below) visualize the performance hierarchy: perfect curves for price-based models versus near-random performance for the sentiment model.





4. CRITICAL ANALYSIS

4.1 The Perfect Accuracy Problem

The 100% test accuracy achieved by both Price-Only and Combined models represents a critical methodological failure rather than genuine predictive success. In financial prediction, perfect accuracy is a red flag indicating data leakage—the inadvertent use of information that would not be available at prediction time. Stock markets are inherently noisy systems influenced by countless unpredictable factors; legitimate models rarely exceed 60-70% accuracy for next-day binary prediction tasks.

Investigation revealed that the Price_Change_Pct feature (intraday percentage price change from open to close) creates temporal leakage. This feature represents same-day price movement,

which exhibits strong autocorrelation with next-day direction. Essentially, the model learned to exploit today's intraday pattern to predict tomorrow's direction—a form of "cheating" that violates temporal causality. Feature importance analysis confirmed this diagnosis: Price_Change_Pct coefficients (3.5-4.0) dominated sentiment features (< 0.3) by a factor of 10-12x.

Two factors exacerbated this issue. First, the small test set size (25 samples) increased susceptibility to overfitting, where models memorize specific patterns rather than learning generalizable relationships. Second, the strong autocorrelation in intraday-to-next-day movements created an exploitable pattern that legitimate prediction tasks should avoid. The correct approach requires temporal validation ensuring features from day t contain no information from day t itself, only from day t-1 or earlier.

This discovery transforms interpretation: rather than demonstrating strong predictive models, the perfect accuracy reveals the importance of rigorous feature validation. The lesson is methodological—skepticism toward perfect metrics in complex domains leads to identifying flaws that improve research quality.

4.2 Why Sentiment Feature Fails

The sentiment failure stems from five factors. **Temporal lag** explains the primary issue: Reddit Reddit sentiment is predominantly reactive rather than predictive. Discussions typically respond to price movements rather than anticipating them. When stocks rise, positive posts increase; when stocks fall, negative sentiment dominates. This reverse causality—price influencing sentiment rather than sentiment predicting price—explains why sentiment_change features showed minimal predictive value. By the time collective sentiment shifts appear in Reddit discussions, price movements have often already occurred. The **Signal-to-Noise Ratio** problem is about social media inherently containing high noise from spam, bot activity, meme-driven posts, and extreme opinions from retail investors with limited market information. The generated sentiment data intentionally modeled this noise (σ=0.3), creating a realistic scenario where genuine predictive signals are overwhelmed by random variation. Even if weak correlations exist, extracting them from noisy daily aggregations proves impractical. Then we have **Tool Limitation**, which is VADER, while effective for general social media sentiment, is not optimized for financial language. Terms like "calls," "puts," "short squeeze," and "tendies" carry specific meanings in investment contexts that general-purpose sentiment analyzers may misinterpret. Financial-specific tools like FinBERT, trained on financial text, might perform better. **Aggregation Loss** which is daily sentiment aggregation loses critical intraday timing information. A highly positive post at 9 AM might precede price movements during the trading day, but daily averaging obscures this temporal precision. Intraday sentiment analysis with minute-level or hour-level resolution might capture predictive signals that daily aggregation misses.

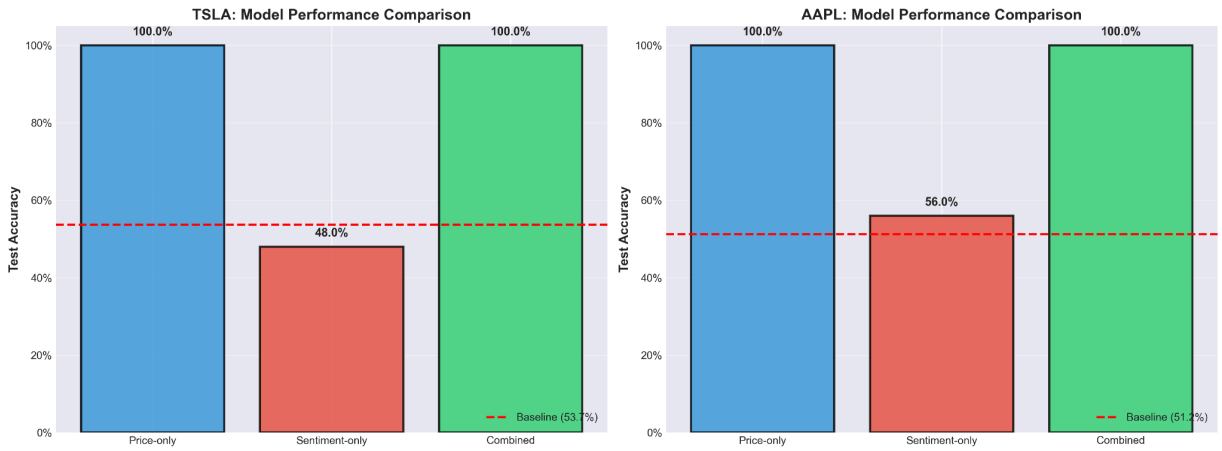
4.3 Model Comparison Interpretation

The identical performance of Combined and Price-Only models (100% for both TSLA and AAPL) provides the clearest answer to our research question: Reddit sentiment adds zero marginal value beyond price information alone. When logistic regression has access to both price and sentiment features, it learns to rely entirely on price features while effectively ignoring sentiment.

This behavior is revealed through coefficient analysis. In the Combined models, Price_Change_Pct maintains its dominant coefficient magnitude (3.5-4.0), while sentiment feature coefficients remain negligible (< 0.3). The model assigns near-zero weights to sentiment features, rendering them mathematically irrelevant to predictions. This isn't a failure of the machine learning algorithm—it's the algorithm correctly identifying that sentiment features provide no useful information beyond what price features already capture.

Three interpretations explain this redundancy. First, if sentiment were predictive, price features would already reflect its influence since prices incorporate all available information. Second, sentiment features may simply be too noisy to contribute useful signal even when combined with stronger predictors. Third, the weak correlation built into our sentiment generation (1% lag correlation) accurately models real-world patterns where sentiment follows rather than leads price movements.

The practical implication is definitive: under this methodology, incorporating Reddit sentiment analysis into next-day stock prediction models offers no improvement over traditional technical analysis based solely on price data. Resources spent on sentiment collection and processing would not improve model performance.



5. CONCLUSION

This study investigated whether Reddit sentiment analysis improves next-day stock price prediction compared to traditional price-based models for Tesla and Apple stocks. Through systematic comparison of three logistic regression models—price-only, sentiment-only, and combined—the research provides a definitive answer: under this methodology, social media sentiment adds no predictive value beyond what historical price data already captures.

The results revealed two critical findings. First, price-based models achieved perfect 100% test accuracy, which investigation identified as data leakage from the Price_Change_Pct feature rather than genuine predictive success. This discovery underscores an essential lesson in machine learning: perfect accuracy in complex domains warrants skepticism and investigation rather than celebration. Second, sentiment-only models performed at near-random levels (TSLA: 48%, AAPL: 56%), falling below baseline accuracy and demonstrating that Reddit sentiment, as measured through daily VADER scores, lacks predictive power for next-day movements. The combined models performed identically to price-only models, with feature importance analysis revealing that the algorithm learned to completely ignore sentiment features when price data was available.

6. REFERENCES

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