UNIVERSITI TEKNOLOGI MALAYSIA

PREDICTING STOCK MARKET TRENDS USING MULTI-SOURCE SENTIMENT ANALYSIS AND ADVANCED DEEP LEARNINGALGORITHMS

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Innovating Solutions

OUTLINES

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INTRODUCTION

- Accurate prediction of stock market movement is very crucial for decreasing investment risks and increase profit
- Stock prices are affected by economic, political, social and psychological factors
- Traditional models rely on historical data but ignore sentiment-driven fluctuations
- Sentiment analysis from news articles and social media posts can help to predict market movements

Problem Statement

- Traditional stock prediction models rely solely on numerical data, missing sentiment impact.
- Some Machine Learning models are computationally efficient but often cannot handle non-linear high-dimensional multi-featured data efficiently
- Some advanced Deep Learning models are expert in handling complex data but show less accuracy
- So, there is always a dilemma choosing between models

Research Objectives

- To enhance the comprehensiveness of prediction by collecting and preprocessing sentiment data
- To implement FinBERT for detailed sentiment analysis and develop LSTM networks for improving prediction accuracy
- To rigorously assess the model's performance with a number of evaluation metrics such as Accuracy, Precision, Recall, F1 score etc

Literature Review

Traditional Stock Market Prediction:

•Early models: ARIMA (Box & Jenkins, 1970)
•GARCH (Engle, 1982)
•Linear Regression (Fama & French, 1992)

•Limitations:
•Cannot capture sentiment,
•poor adaptability to financial market fluctuations.

Machine Learning Approaches:

(Huang et al., 2005; Chen et al., 2013).
•Decision Trees,
•Random Forests, and
•SVMs

•These models work well with structured data
•fail with textual sentiment.

Literature Review

Sentiment Analysis & Financial Markets:

•Sentiment plays a crucial role in stock price movement
(Loughran & McDonald, 2011)

•Studies show financial sentiment can predict stock market trends
(Bollen et al., 2011).

Deep Learning & NLP Models:

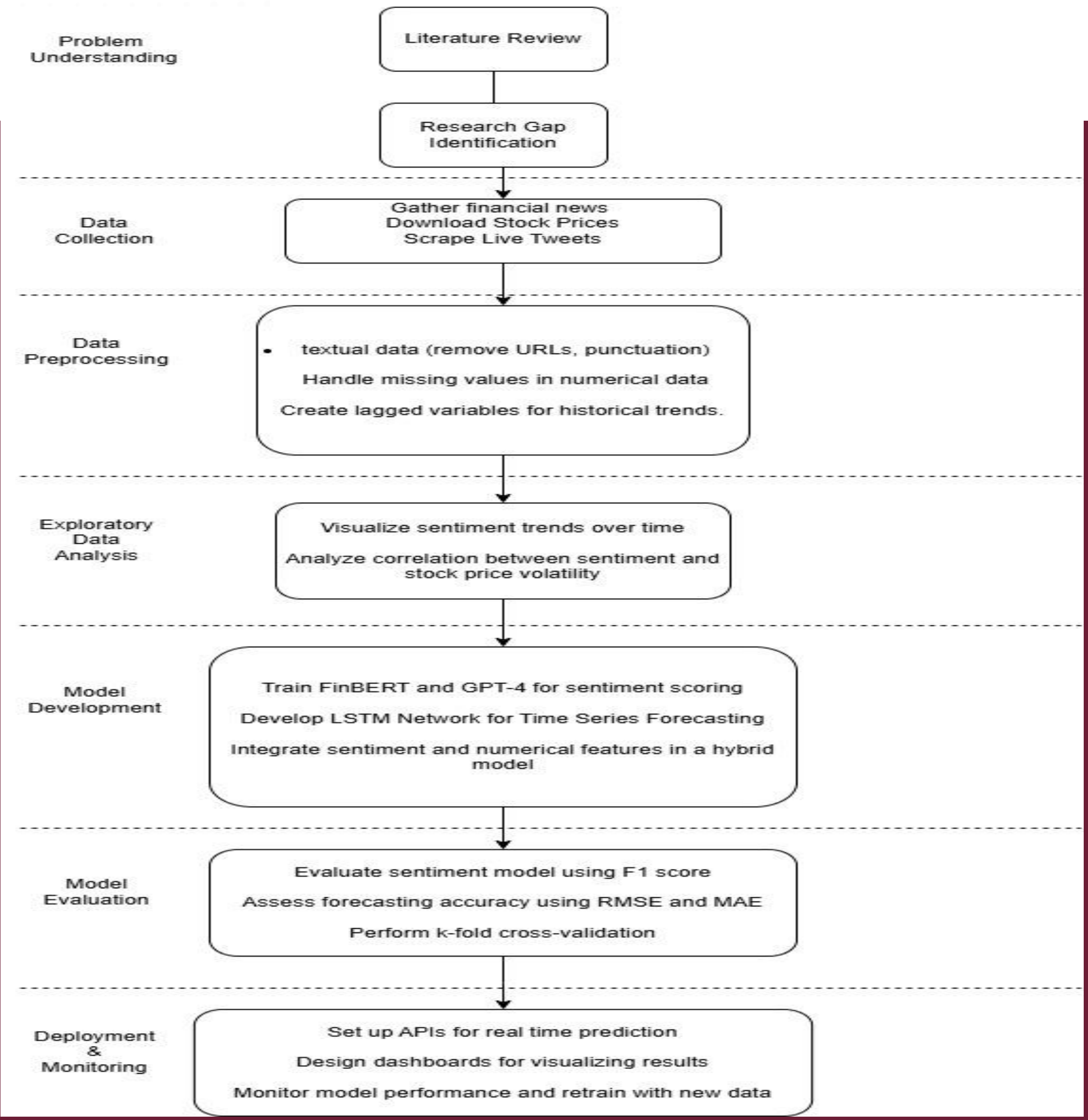
•**FinBERT** outperforms traditional sentiment models
(Araci, 2019).

•**GPT-4** can extract complex sentiment cues but has computational constraints
(Brown et al., 2020).

•**LSTM** effectively captures sequential dependencies in stock trends
(Fischer & Krauss, 2018).

Research Methodology

- **Step-by-step approach followed in this study:**
  🔷 **Step 1:** Data Collection (**Stock Prices + Financial News**)
  🔷 **Step 2:** Data Preprocessing (**Cleaning, Feature Engineering**)
  🔷 **Step 3:** Sentiment Analysis (**FinBERT**)
  🔷 **Step 4:** Machine Learning Model
  🔷 **Step 5:** Evaluation & Results



Research Methodology

Data Collection

- Stock Market Data: 15 NYSE-listed companies stock price for a period of 20 years
- Sentiment Data: Financial news headlines from CNBC

- Challenges Faced
  Original plan was to collect both data for 20 years, but sentiment data spanning 20 years was not found. So sentiment datset limited to 2018-2020

Research Methodology

Stock Data Preprocessing

- Handling missing values, outliers
- Creating technical indicators & lag features

Sentiment Data Preprocessing

- Text Cleaning: Removing special characters, stopwords
- Tokenization and Lemmatization

Initial Findings(EDA)

Feature Engineering

1. Stock Based Features

- Lagged Prices – Previous stock prices as inputs
- Technical Indicators – Moving averages, volatility, momentum indicators

2. Sentiment-Based Features

- Aggregated Sentiment Scores over rolling time windows
- Sentiment Trends - Capturing fluctuations in market mood

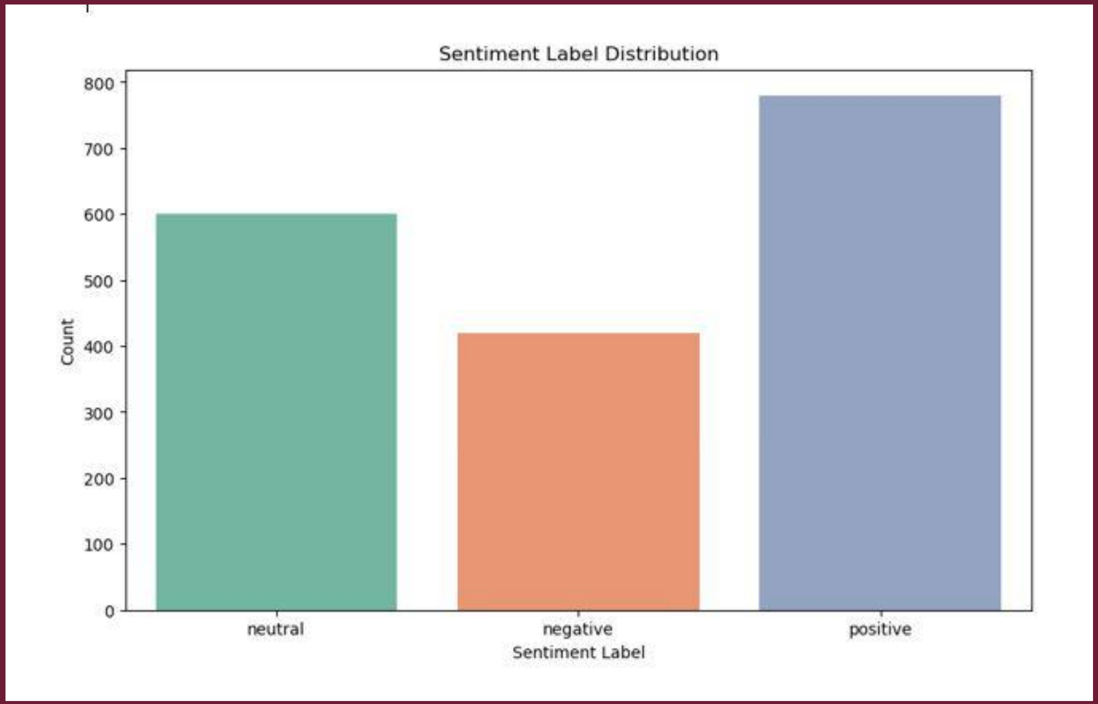
Initial Findings(EDA)

Sentiment Classification Using FinBERT

- FinBERT assigns **positive, neutral, or negative** labels to headlines
- Helps understand **market sentiment trends**

Why FinBERT?

- Pretrained on **financial texts**, outperforming general sentiment models.
- **Understands market-specific language** better than traditional NLP.



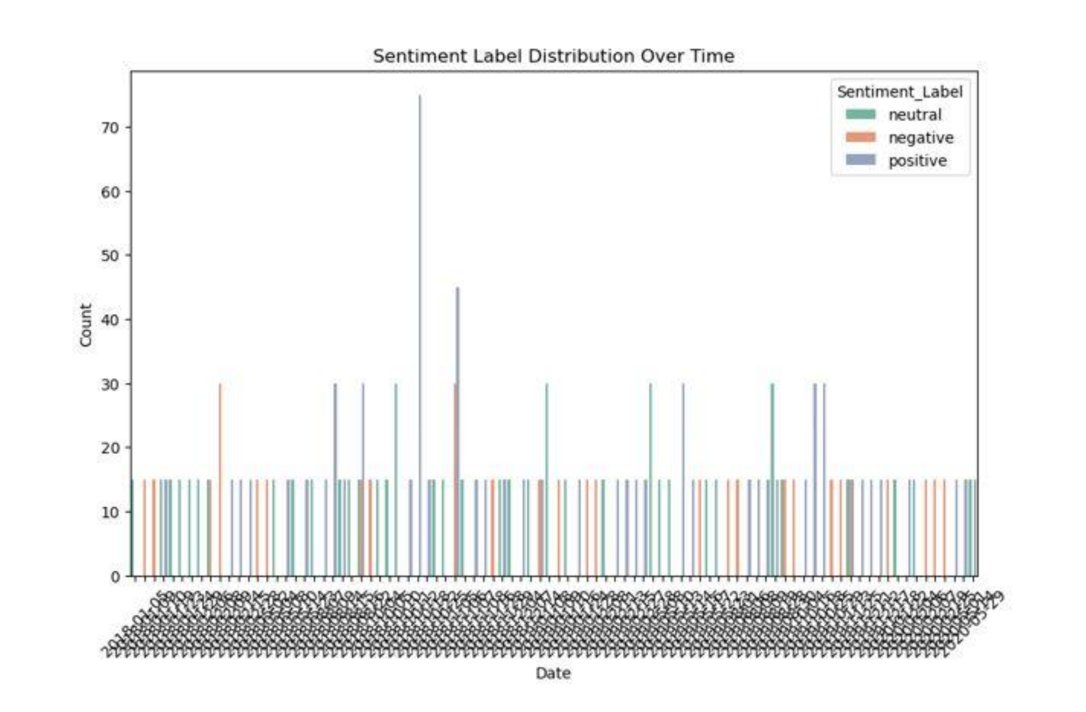
Initial Findings(EDA)

Key Observations

- Negative sentiment is more frequent during financial crises or downturns.
- Periods of high positive sentiment often precede stock price surges.
- Neutral sentiment dominates in stable market conditions.

Why This Matters?

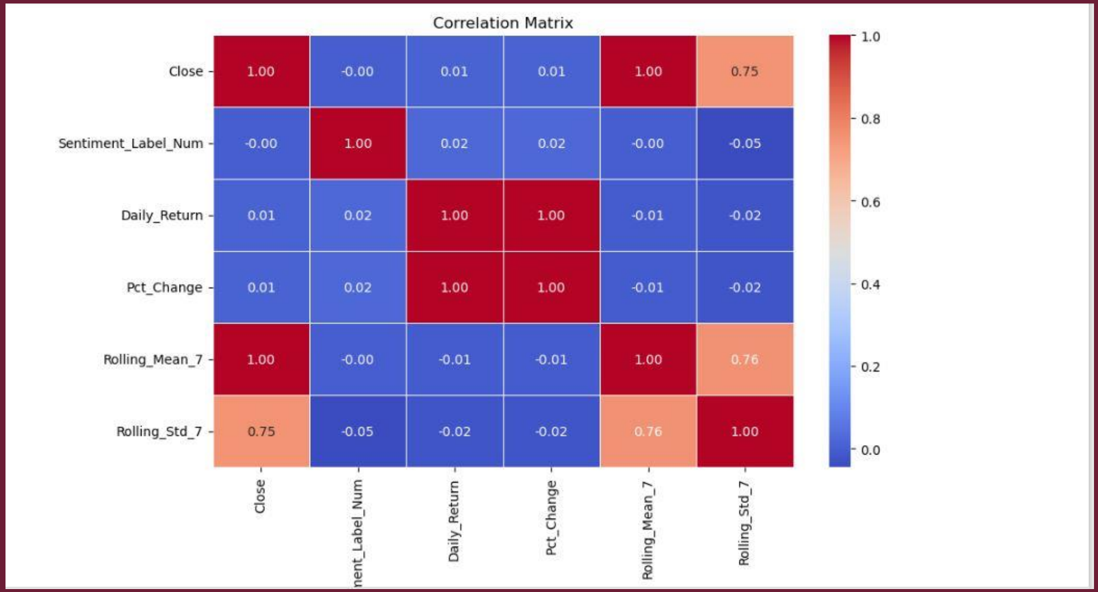
- Understanding sentiment trends helps predict market movements.
- Sentiment shifts can serve as an early indicator of volatility



Initial Findings(EDA)

Correlation Between Sentiment & Stock Returns

- Merged daily sentiment scores with corresponding stock returns.
- Analyzed positive, neutral, and negative sentiment impact.
- Positive sentiment correlates with short-term stock price increases.
- Negative sentiment correlates with stock price drops and volatility spikes.
- Neutral sentiment has minimal impact on daily stock returns.



Model Development

- **Machine Learning Model Selection**

Reasons for choosing Random Forest:

- Handles structured stock data well.
- Can incorporate both numerical (stock indicators) & categorical (sentiment labels) features.
- Robust against overfitting.

Model Development

- **Model Training & Testing**

- Train-test split: 80% training, 20% testing.
- Feature Scaling: Standardized stock price data.
- Sentiment Labels: Converted into numerical values for ML models.
- Random Forest trained using stock indicators + sentiment features.

Model Development

Model Performance Evaluation

Key Metrics Used for Evaluation:

- Accuracy – Measures how often the model correctly predicts stock movement.
- Precision & Recall – Evaluates how well the model identifies positive and negative trends.
- F1 Score – Balances precision and recall for overall performance assessment.

Model Development

- Stock Price Forecasting with and without Sentiment
  Random Forest (without sentiment): Lower accuracy due to missing external influences.
  Random Forest (with sentiment): Improved accuracy as sentiment added predictive value.
- Accuracy Scores of Different Models
  Random Forest (Stock Data Only): 51.35%
  Random Forest (Stock + Sentiment Data): 71.83% (Improvement)

- Sentiment integration improved stock movement prediction accuracy.

Discussion & Future Works

Achievements

- Combines sentiment analysis with machine learning for better predictions.
- Uses FinBERT, a finance-specific sentiment model for accuracy.
- Prediction accuracy is improved.

Limitations

- Sentiment dataset limited to 2018-2020 (original plan was 20 years).
- Real-time market predictions not implemented yet.
- Stock market unpredictability remains a challenge despite improved accuracy.

Discussion & Future Work

Future Work

- Expand data sources: Include social media (Twitter, Reddit) for better sentiment tracking.
- Test deep learning models: Transformer-based models (GPT-4, BERT variants).
- Develop real-time prediction systems: Implement sentiment-driven trading strategies.
- Use alternative financial sentiment datasets: To improve training data diversity.

Potential Applications

- Investment firms and traders can use sentiment-enhanced models for better decision-making.
- Automated trading systems could incorporate real-time sentiment analysis.

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