PREDICTING MARKET REACTIONS TO FINANCIAL NEWS EVENTS USING NATURAL LANGUAGE PROCESSING (NLP) AND DEEP LEARNING TECHNIQUES

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This research is aiming at predicting market reactions to financial news events such as Non-Farm Payroll (NFP), Consumer Price Index (CPI), and Federal Open Market Committee (FOMC) announcements immediately after the release of such news using Natural Language Processing (NLP) and Deep Learning Techniques.

BACKGROUND

Financial news events have a significant impact on market dynamics which influence investor sentiment and shape market trends. In the US, events such as Non-Farm Payroll (NFP) can make the US equity market experience a 1% and 2% movement in the S&P 500 on the day of the announcement (Boyd et al., 2005). Nevertheless, events such as wars and conflicts can cause an increase in market volatility. The VIX index commonly spikes during such times, reflecting increased market uncertainty (Bekaert and Hoerova, 2014). The issue dwells on how responsive market reactions are towards financial news events and how to predict a market reaction after a financial news event.

Several studies have been done on the role of Natural Language Processing (NLP) in financial forecasting. Stock Forecasting using NLP combines linguistics, machine learning, and behavioral finance (Xing et al., 2018). Sentiment analysis is a popular NLP technique used for financial forecasting (Cambria, 2016). It involves interpreting and classifying emotions in text data. In this study, market sentiments that impact information flow and trade are the text data to be classified. Fazlija and Harder (2022) showed that BERT-based sentiment analysis has the potential to forecast the direction of the Standard & Poor 500 index based on financial news.

Other studies highlight the use of deep learning models, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) networks, and Convolutional Neural networks (CNN), in processing financial text data for market prediction, with variable degrees of success depending on the data and model complexity. LSTM networks and GRU networks are two advanced types of recurrent neural networks (RNNs) designed to handle sequential data and overcome the limitations of standard RNNs, particularly those related to learning long-term dependencies. LSTM is a powerful model that does so well in analyzing sequential text data (Yu et al., 2019). On the other hand, GRU is efficient but cannot be taught to count or solve context-free language (Weiss et al., 2018), nor does it work for translation (Britz et al., 2017). However, GRU tends to outperform LSTM in scenarios involving long text and smaller datasets, whereas LSTM does better in other circumstances, notably with larger datasets (Yang et al., 2020). Finally, a convolutional neural network uses a non-linear activation function to apply convolutional operations, followed by a full connection layer for classification. The combination of CNN without activation function and LSTM or its variant has better performance (Luan and Lin, 2019).

The impetus for this study originated from a gap in the existing literature on the impact of news events on financial markets, namely the use of natural language processing (NLP) approaches such as LSTM, GRU, and CNNs. This study seeks to close this gap by investigating the efficacy of various models in analyzing market reactions to news events. This research proposes to develop a predictive model to predict outcomes from market reactions to financial news events with the help of deep learning and natural language processing, using NLP-based sentiment analysis to investigate the impact of these news events on market volatility and price direction, as well as historical financial news and market price data to build predictive models using Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNNs), and compares the performance of these models in predicting the immediate market reaction to financial news releases.

Research Description and Anticipated Outcomes

Research Description

The purpose of this research work is to develop a model that can effectively forecast market reactions to financial news with the help of deep learning and natural language processing (NLP) techniques. The research focuses on using sentiment analysis based on NLP to assess the impact of news events on market volatility and price direction. The study proposes to use historical financial news and market price data from various financial data platforms such as Forex factory to train and test predictive models based on Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks. For this project, we will focus on the GOLD instrument. The research will involve the comparison of the performances of the models utilized for this research in predicting immediate market reactions to new releases. This will be done to assess the best-performing model by various metrics.

Methodology

Data Collection:

Data is collected from various financial data platforms. Forex Factory provides financial news data for events such as Non-Farm Payroll (NFP), Consumer Price Index (CPI), and Federal Open Market Committee (FOMC). This information will include news stories, press releases, and social media posts from financial analysts. Market price data, such as currency pairs, will be acquired from MetaTrader using the MetaTrader API to correlate news sentiment with market reactions.

Data Preprocessing:

Data wrangling and preprocessing will be conducted after data collection. Preprocessing of the acquired textual data will include tokenization, stop word removal, stemming, lemmatization, and vectorization with techniques like TF-IDF or BERT embeddings. Market data will be synchronized with the timing of news events to achieve precise alignment for model training.

Model Development:

Sentiment Analysis: BERT or other advanced models will be used to assign sentiment scores to news stories. These sentiment models will transform qualitative text data into quantitative scores.

Predictive Modelling: Three different models will be developed in this research and a comparison of model performances will be conducted. The following models will be used:

LSTM: This is a type of neural network that can handle sequential input and is effective for making predictions over time.

GRU: This is a simplified variation of LSTM that can achieve comparable performance at a lower computational cost.

CNN: This is a deep learning model used to extract features from text data and adds another layer of analysis when paired with temporal data.

These models will be trained on historical financial data to predict market reactions by combining sentiment ratings with previous market data.

Evaluation:

The models' performance will be measured using measures such as accuracy, precision, recall, and F1-score. The model predictions will then be compared to actual market results to determine their practical utility.

Anticipated Outcomes:

The project is expected to produce a predictive model that successfully forecasts the market's rapid reaction to Non-Farm Payroll (NFP), Consumer Price Index (CPI), and Federal Open Market Committee (FOMC) news releases.

The study expects to show that NLP-based sentiment analysis may greatly increase market forecast accuracy, especially when combined with deep learning models such as LSTM, GRU, and CNN. A comparison of LSTM, GRU, and CNN models will provide the most effective method for real-time market prediction using financial news sentiment.

The study also anticipates that the comparative analysis will reveal each model's strengths and weaknesses in various market scenarios. LSTM and GRU will be expected to excel in handling sequential data and CNNs potentially will show strong performance in text classification tasks related to market prediction.

These findings will add to the existing literature by shedding light on how effective the various deep learning models in financial market forecasting will potentially lead to better investing strategies and risk management techniques.

The research will improve our understanding of natural language processing (NLP) applications in financial forecasting, as well as provide useful tools for traders, analysts, and persons who are interested in trading in real-time.

References

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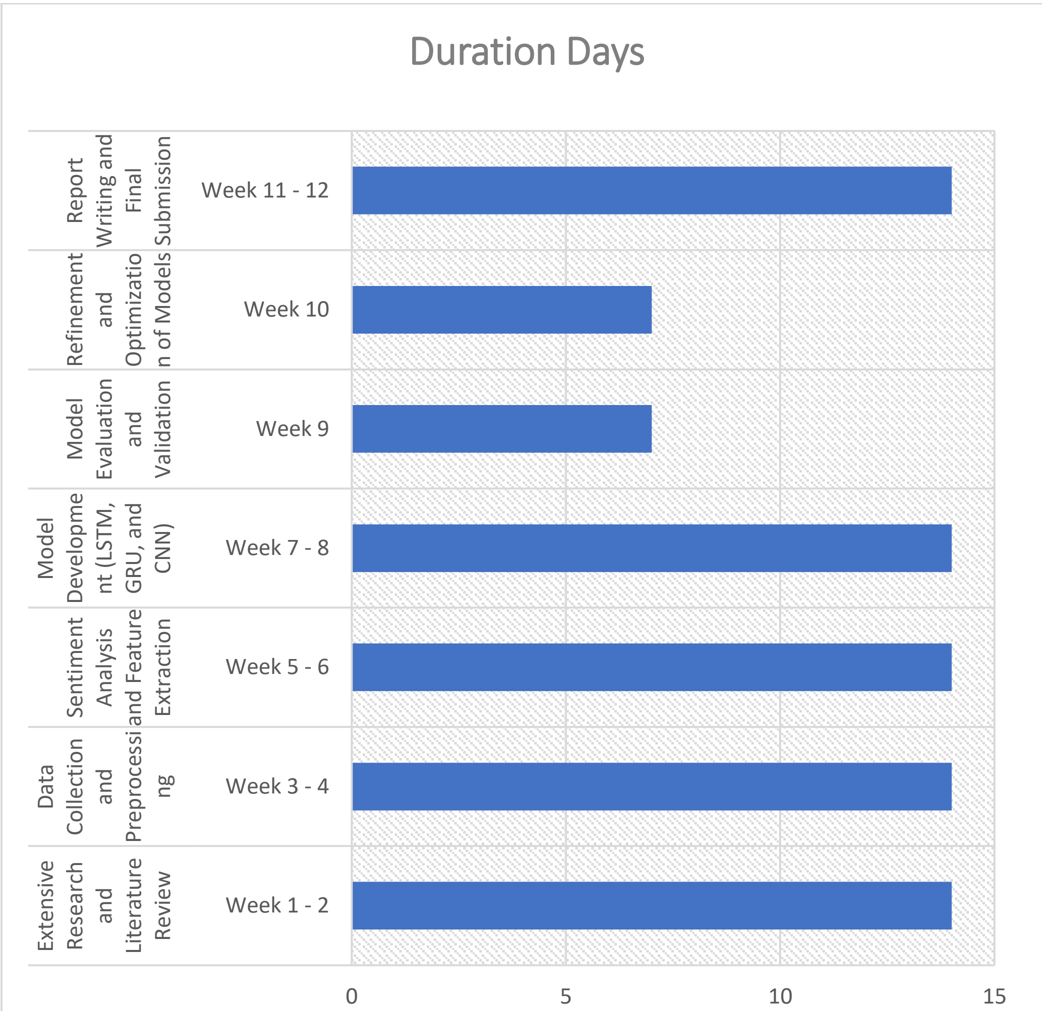
Timeline (Gantt Chart)

The project will be broken down into the following tasks:



Timeline Justification:

Weeks 1-2: Extensive Research and Literature Review

An in-depth literature review on using NLP in financial markets with a focus on sentiment analysis and predictive modeling will be conducted. This will take 2 weeks.

Weeks 3-4: Data Collection and Preprocessing

This step is an important procedure and might require time because machine learning models require good and high-quality data. This will take 2 weeks.

Weeks 5-6: Sentiment Analysis and Feature Extraction

Sentiment Analysis and Feature extraction would take two weeks to complete.

Weeks 7-8: Model Development (LSTM, GRU, and CNN)

An ample amount of time is required to train the LSTM, GRU, and CNN models which would take 2 weeks.

Weeks 9: Model Evaluation and Validation

Evaluation of the performance of each model using appropriate metrics and a comparison of their effectiveness will be conducted and will take a week.

Week 10: Refinement and Optimization of Models

Models will be refined based on evaluation and the hyperparameters of the models will also be optimized. This will take a week.

Weeks 11-12: Report Writing and Final Submission

The research findings will be compiled this week and a final report will be prepared and submitted. Compilation and drafting of the final report will take two weeks.

Risk Assessment and Contingencies

RISK	DESCRIPTION	CONTIGENCY
Data Quality Issues	Poor quality data might result in erroneous sentiment analysis and model predictions.	Implementation of rigorous data cleaning and preprocessing procedures (deleting duplicates and dealing with missing values). Discovery and incorporation of new data sources to provide a strong dataset.
Model Performance	The predictive models (LSTM, GRU, CNN) may underperform, yielding low accuracy or unreliable predictions.	Tuning of hyperparameters and Investigation of ensemble techniques or the use of alternate architectures or addition of new features to improve model performance
Technical Challenges	Integration with the MetaTrader API or other technical components may pose difficulties, resulting in delays in data gathering and processing.	Additional time in the timeline for troubleshooting technical issues. Access to technical support and documentation. Exploration of alternative APIs or data sources as a backup.

Time Management	The complexity of the project may cause tasks to take longer than expected, potentially delaying project completion.	Implementation of a buffer period in the timeline to accommodate unforeseen delays. Prioritizing Critical tasks and parallel processing of tasks where feasible
Ethical Considerations	Potential ethical considerations around the use of financial data, particularly in the context of sensitive market forecasts.	Compliance with all relevant data privacy regulations and ethical guidelines. Obtaining ethical clearance before beginning the project and continually monitoring the ethical implications of the research.

Ethical Considerations

This project will use publicly available financial data and news, while adhering to data usage policies. No personal or sensitive data will be used. Ethical clearance will be acquired prior to data collection.