Deciphering Bitcoin Price Movement:
Unraveling the Influence of Twitter Sentiment, Google trend, and Fear and Greed Index

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This thesis is submitted in partial fulfillment of the requirement for the degree of Master of Science in Data Analytics and Design Thinking for Business

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DECLARATION

It is hereby declared that the work contained in this thesis is original. The information derived from the literature or work has been duly acknowledged and presented in the reference section. No part of this thesis has been submitted elsewhere for any other degree, diploma, or similar titles of recognition.

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LIST OF ABBREVIATIONS

CFGI	Crypto Fear and Greed Index
API	Application Programming Interface
NLP	Natural Language Processing
VADER	Valence Aware Dictionary and Sentiment Reasoner
BERT	Bidirectional Encoder Representations from Transformers
FinBERT	Financial Bidirectional Encoder Representations from Transformers
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
RF	Random Forest
CNN	Convolutional Neural Network
GLUE	General Language Understanding Evaluation
MultiNLI	Multi-Genre Natural Language Inference
SMOTE	Synthetic Minority Over-sampling Technique
RELU	Rectified Linear Unit
RMSprop	Root Mean Square Propagation
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve

ABSTRACT

Bitcoin, the most popular decentralized cryptocurrency, greatly influencing the global economic landscape since its inception in 2008. The cryptocurrency, known for its dynamic transparency and independence from intermediaries, gets driven by its volatility and market sentiment. This study explores to unravel the influence of sentiment indicators derived from Twitter, Google Trends, and the Crypto Fear and Greed Index (CFGI) on Bitcoin price movements using deep learning models. Specifically, Bidirectional Encoder Representations from Transformers (BERT) and Financial Domain Specific Bidirectional Encoder Representations from Transformers (FinBERT) are implemented to extract sentiment scores and labels, and Long Short-Term Memory (LSTM) is implemented for price direction prediction. LSTM on BERT and LSTM on FinBERT achieved an overall accuracy of 0.85 and 0.86, respectively, for next day price movement prediction whereas, for next month predictions, the accuracy reached up to 0.94 and 0.93, respectively. The study identified significant influence of sentiment features on weekly and monthly price movement prediction. However, no added advantage of using FinBERT over BERT for extracting twitter sentiment was observed.

Keywords: Bitcoin, cryptocurrency, sentiment analysis, deep learning, LSTM, BERT, FinBERT, price movement prediction.

CHAPTER -1
INTRODUCTION

1.1 Background of Research

Bitcoin, a decentralized cryptocurrency, created in 2008, has disrupted the global dynamics of financial market. It is known for its decentralized, secured and transparent nature by using blockchain technology which enables the users to transect independently without the need of any intermediator, central bank and government. It has opened boundaries for fast and secured financial transaction.

In 2010, the value of bitcoin was approximately $0.40, whereas it reached all time high of around $73,000, with a market capitalization of approximately $1.44 trillion in 2024 **[1] [2]**. This indicates that the popularity and adoption of bitcoin is increasing tremendously over the years. Even though many countries banned bitcoin at the early stage, they have started to adopt it after encountering the growing popularity and realizing the future prospect of it.

However, the cryptocurrency market is an unregulated and emotion driven which makes it a highly volatile market for investors. Moreover, the whole market is mostly dominated by bitcoin's price movement. In making investment decisions, many retail investors rely on sentiments from Social media, Google search, and Crypto fear and greed index (CFGI) besides the technical indicators **[3]**. As the market is categorized by emotional behavior, evidence suggests that returns and volatility are greatly associated with market sentiment **[4]**. So, it is crucial for investors to identify the sentiment factors influencing the price direction of bitcoin to understand market movement.

Several researches have already been studied on the bitcoin price prediction focusing mainly on the correlation between bitcoin price and other commodities price **[5]**. The results from these studies didn't show any strong correlation between bitcoin and other commodities such as gold, stock market index etc. Some researchers adapted a modern approach of predicting bitcoin price by implementing machine learning and deep learning algorithms which appears to be a more appropriate approach in determining bitcoin price direction **[6]**.

1.2 Problem Statement

In the cryptocurrency market, many retail investors make investment decisions based on market sentiments. The mostly used sentiment factors are Twitter sentiments, Google Trend and CFGI. Before investing in a highly volatile market based on sentiments, it is necessary to understand whether these sentiments have any influence over the price direction of bitcoin and if so, how significant that influence is.

However, deriving sentiments from textual data which are in an unorganized form is a highly complex task. The analysis of the influence of twitter sentiments over bitcoin price highly depends on how accurately the sentiments are extracted from the tweets. Moreover, it is crucial to identify how these sentiments influence the bitcoin price movement over different timeframes.

This study focuses on unraveling the influence of these sentiments on bitcoin price direction over different timeframes. Further, it aims to identify patterns on the price movement of bitcoin over different timeframe so that investors can be aware of whether they should make any investment decision based on these sentiments.

1.3 Research Goal

The primary goal of this research is to identify any underlying influence of sentiment indicators over bitcoin price movement using deep learning algorithms. State-of-the-art deep learning models, BERT and FinBERT will be implemented for extracting sentiments from tweets. These models are built on transformer architecture, a type of neural network designed for handling sequential data, which is proved to be highly effective in natural language processing (NLP) tasks.

After extracting the sentiments, LSTM, a type of recurrent neural network (RNN) designed for predicting sequential and time-series data, will be implemented to predict bitcoin price direction across different timeframes. LSTM will be applied separately on BERT sentiments along with Google trends and CGFI data as well as FinBERT sentiments with Google trends and CGFI data across various timeframes.

Finally, the study will compare and evaluate the performance between LSTM with BERT model and LSTM with FinBERT model, aiming to determine the best performing model and the influence of sentiment factors on bitcoin price movement.

1.4 Chapter Organization

The study is arranged into five chapters as follows:

- Chapter 1: This chapter introduces the research objectives, background, and significance of the study.
- Chapter 2: This chapter reviews the information available in literatures about this research.
- Chapter 3: This chapter explains the methodology used in the research for dataset collection, data exploration, data pre-processing, and model implementation.
- Chapter 4: This chapter demonstrates the results from the analysis with interpretations.
- Chapter 5: This chapter outlines the conclusion and further work needs of the study.

CHAPTER -2

LITERATURE REVIEW

The Cryptocurrency market has been booming since the last decade, regardless of its high volatility. Understanding the movement of Bitcoin is crucial for investors, being the most dominant cryptocurrency in the market. The economic value of cryptocurrencies like bitcoin is not completely clear to identify the relevant econometric models [7]. And investors are uncertain about the factors influencing the price movement. Therefore, many scholars have studied the market from numerous alternative perspectives, from using standard econometric models for volatility and volume forecasting, to using tools from systems dynamics [8]. In recent years, the usage of state-of-the-art time series analysis tools, machine learning and deep learning models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs) are getting widely adopted in financial sector as well [9, 10].

Most of the retail investors go through the market sentiments from CFGI, Twitter and Google Trend besides the technical indicators before making any investment decisions. A study [4], on the most popular sentiment indicator in the current market, CFGI, identified a significant positive relationship between CFGI sentiment and Bitcoin investment. The index was developed by the team of "Alternative.me" with a purpose of determining market momentum and volume, volatility, social media momentum, and Bitcoin dominance using a single indicator. It indicates current market sentiments in five levels: Extreme fear, Fear, Neutral, Greed, and Extreme Greed, ranging from 0-100, where the lower value indicates fearful condition of the market and the higher value shows that upward momentum of the market.

On the other hand, Twitter is the most popular social media platform for discussions and announcements related to cryptocurrencies. The authors of a study [11] stated that, on 24 March 2021, when Elon Musk tweeted that Tesla would accept Bitcoin for payments, Bitcoin price surged by 5.2 percent. On the contrary, the price of Bitcoin fell by 9.5 percent on 13 May 2021 when Elon Musk tweeted questioning the energy consumption of mining Bitcoin. Therefore, tweets have been a great influencer of market sentiments. There are many machine learning models that can be used to extract sentiment from textual data like tweets. A study on Bitcoin

Volatility Forecasting with Twitter Data [8], focused on predicting bitcoin price volatility using classical econometric model and deep learning model suggested that implementing a complex embedding structure model such as BERT, instead of VADER model to extract sentiments from tweets, could improve the prediction accuracy of bitcoin price movement.

A group of google researchers [12], designed BERT, a conceptually simple yet empirically powerful natural language representation model, to pretrain deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. Their research resulted in a state-of-the-art pre-trained BERT model that can be finetuned with just one additional output layer to produce models for various tasks, for instance, question answering and language inference, without making any task specific extensive modifications in the architecture. The model scored 80.5% and 86.7% accuracy with absolute improvement of 7.7% and 4.6% in GLUE and MultiNLI respectively [12]. However, in financial context, BERT pretrained models for general purposes found questionable in accurately embedding words like ‘chart’, ‘hold’, ‘bull’ or ‘bear’, which are frequently used in financial context [11].

Later on, another group of researchers [13], came up with an objective to develop FinBERT, another state-of-the-art large language model, customized on Google’s BERT algorithm, to learn financial contextual information from text data. In recent studies, while comparing its performance with other machine learning algorithms, namely, support vector machine (SVM), random forest (RF), convolutional neural network (CNN), long short-term memory (LSTM), and Google’s original BERT model, it was unclear on whether it beats these algorithms in terms of performance. However, further research concluded that FinBERT surpasses other algorithms in classifying positive or negative sentiment of sentences that were previously mislabel as neutral by other models. The reason behind its improved sentiment classification of text is its ability to identify the underlying financial context of the text. Therefore, FinBERT is considered more appropriate deep learning model to extract sentiment from tweets related to cryptocurrencies, as it is pretrained for embedding sentiments from financial texts. However, in this study, both of the models are implemented to explore how they explain bitcoin price movement combined with LSTM model.

LSTM (Long Short-Term Memory) is a type of module with recurrent consistency generally provided for RNN models. It can manage the memory at each input better than RNN as it uses memory cells and gate units efficiently. The ability of LSTM model has been found superior in learning long-term dependencies in a series, which is used greatly in financial time series forecast [14]. With the increasing popularity among researchers, A study [15] developed an LSTM model for bitcoin price prediction, found significant improvement over traditional time series analysis tools. Another study on LSTM neural networks [16], utilized its ability to identify long-term dependencies and store both long-term and short-term sequential information, to improve the forecasting techniques of bitcoin prices. The study has observed better prediction outcomes using the LSTM network compared to the performance of other models.

However, many uncertain factors influence the cryptocurrency market for instance, political, economic, environmental incidents, for which, LSTM alone cannot be an appropriate model for producing accurate predictions for bitcoin. Therefore, this paper focuses to acknowledge this limitation by extracting sentiments from twitter using BERT and FinBERT, then implement LSTM model to analyze whether tweet sentiments, CFGI sentiments, Google trend sentiments has any impact on the price movement of the bitcoin across various timeframes.

CHAPTER - 3
METHODOLOGY

3.1 Data Collection and Preparation

The data used in this research are collected from multiple sources. As different sentiment factors are used in this study, they had to be collected from different source using API. The primary datasets are:

- **Twitter Sentiment Data:** Around 4.5 million tweets about Bitcoin were sourced from Kaggle, containing around 8,000 tweets per day from the period of January 2021 to June 2022. [17]
- **Bitcoin Historical Prices:** Hourly historical price data of Bitcoin was collected from Kaggle for the same period. [18]
- **Google Trends Data:** Google keyword search data of word "Bitcoin" was collected using the SerpAPI from January 2021 to June 2022.
- **Crypto Fear and Greed Index (CFGI):** The CFGI data was gathered using the "Alternative.me" API from January 2021 to June 2022.

These datasets were primarily collected and needed to be cleaned and prepared for the analysis.

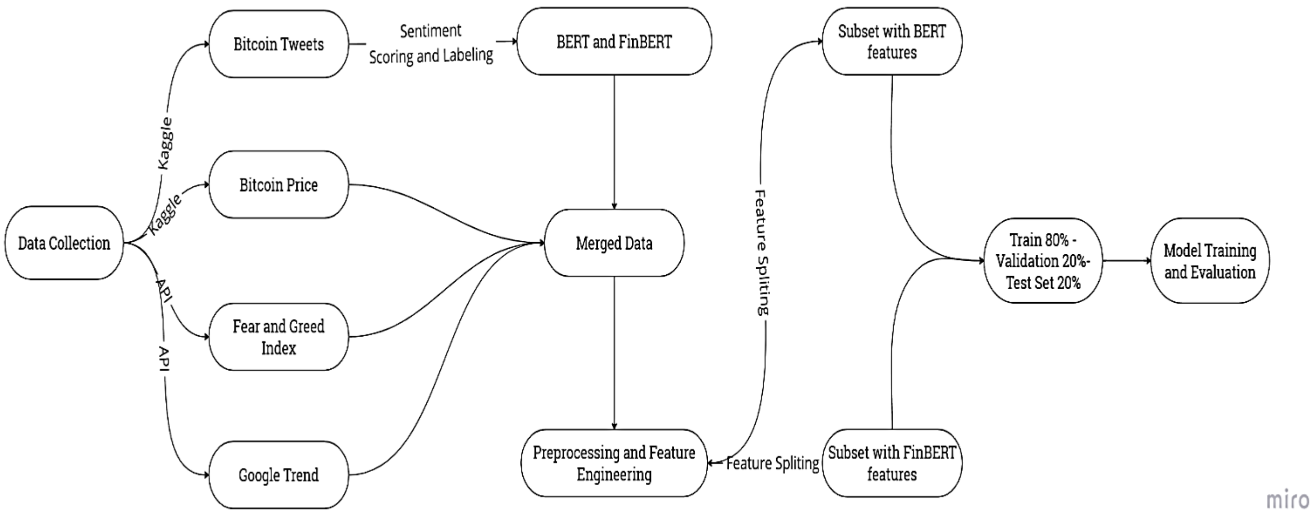

Figure 3.1 Idea Architecture

3.2 Feature Engineering

At First, the data were checked and stored in appropriate datatype format. Then, new features were created to enrich the analysis:

New features were created in the Bitcoin price dataset for percentage change in price over different timeframes using the hourly price dataset, these features are:

- 1-day Change: Percentage change in Bitcoin price in the next day.
- 7-day Change: Percentage change in Bitcoin price in the next seven days.
- 30-day Change: Percentage change in Bitcoin price in the next thirty days.

Moreover, the target variables were engineered in 3 classes, 1, 0, and -1:

- Next 1-day Movement: 2 if the price increased by more than 2%, 1 if was in a stable range of 2%, and 0 if price decreased by more than 2% over the next day.
- Next 7-day Movement: 2 if the price increased by more than 5%, 1 if was in a stable range of 5%, and 0 if price decreased by more than 5% over the next day.
- Next 30-day Movement: 2 if the price increased by more than 10%, 1 if was in a stable range of 10%, and 0 if price decreased by more than 10% over the next day.

3.3 Sentiment Scoring and Labeling

Here, two state-of-the-art model BERT and FinBERT model were used for sentiment classification and scoring. The process involves the following steps:

- **Text Cleaning:** First, the tweets texts are cleaned by URLs, hashtags, mentions, special characters and emojis.
- **Tokenization:** The process of splitting the texts into smaller units is called tokenization, where every single word is a token.
- **Input Representation:** The models then include token IDs, segment IDs, and attention masks for each token.
- **Sentiment Classification:** Finally, the processed texts go through the pre-trained model to generate sentiment label and scores for each sentiment. In this study, the tweets were classified into positive or negative sentiments.

BERT: Bidirectional Encoder Representations from Transformers

BERT is a state-of-the-art language representation model developed by a group of Google researchers. It has ability to understand context in texts better than any other models of natural language processing (NLP). Traditional models read text sequentially (left-to-right or right-to-left), whereas BERT processes text bidirectionally. It reads the whole sentence at once, which allows it to understand the context of a word based on the position of other words sitting before and after of that particular word. This unique approach helps the model to capture sentiment of a text using a more comprehensive context.

Furthermore, it is built on the transformer architecture, which can handle wide-range of dependencies and relate to different parts of the text using self-attention mechanism.

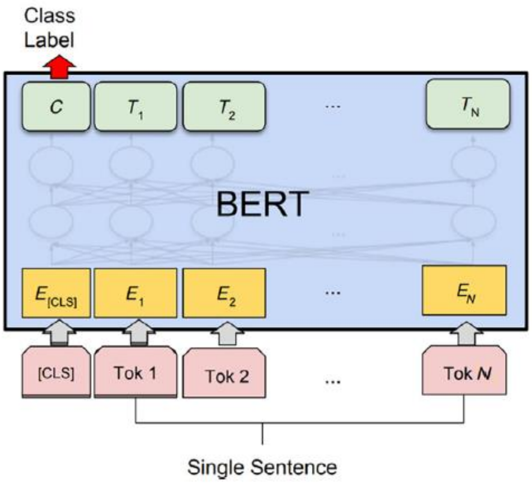

Figure 3.2: *Fine-tuning of the BERT algorithm used for single sentence classification [12]*

Here, the popular pretrained BERT model, base-case-uncased is applied on the tweet texts, which is pre-trained on a large corpus of text suitable for sentiment understanding using unsupervised learning.

FinBERT: A Financial Domain-Specific Variant of BERT

FinBERT is a fine-tuned variant of BERT model developed for financial sentiment analysis. It is designed to capture the tones and jargon that are specifically used in the financial context. BERT is pre-trained on a general corpus of texts, whereas FinBERT is further fine-tuned with a large corpus of financial texts. This supplementary training helps FinBERT model to better understand the context of financial language.

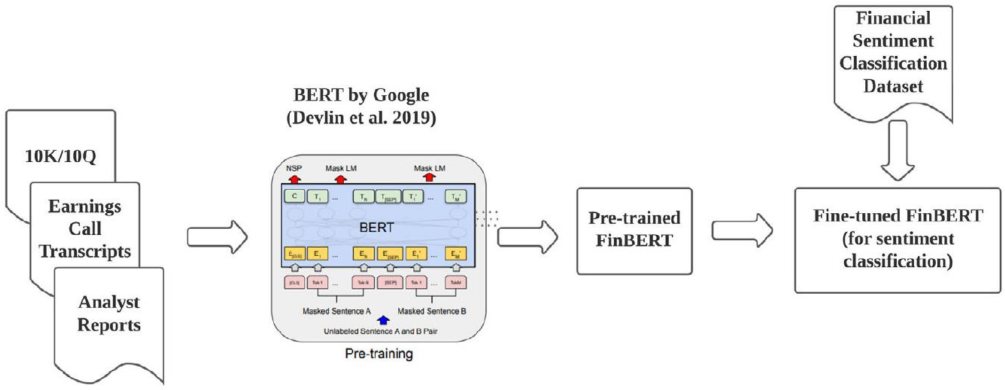

Figure 3.3 *FinBERT pretraining and fine-tuning (for sentiment classification) [13]*

Therefore, it is the most suitable model for extracting sentiments from financial texts, like financial news articles, financial reports, and social media posts about financial topic. Here, the popular pretrained FinBERT model, ProsusAI is applied on the tweet texts.

Finally, after the completion of sentiment labeling and scoring, the scores are aggregated on hourly basis and merged with hourly bitcoin price and other sentiment data.

Table 3.1: Dataset Description

Feature	Data Type	Description
datetime	Date/Time	The hourly date and time of bitcoin price
price	Numeric	The current price of the asset Bitcoin.
24h_change	Numeric	Percentage change in Bitcoin's price over the last 24 hours.
7d_change	Numeric	Percentage change in Bitcoin's price over the last 7 days.
30d_change	Numeric	Percentage change in Bitcoin's price over the last 30 days.
next_1d_movement	Target Category	The direction of the price movement occured next day, 0 for downward, 1 for stable, 2 for upward.
next_7d_movement	Target Category	The direction of the price movement occured next week, 0 for downward, 1 for stable, 2 for upward.
next_30d_movement	Target Category	The direction of the price movement occured next month, 0 for downward, 1 for stable, 2 for upward.
fng_value	Numeric	The Fear and Greed Index value.
fng_class	Categorical	The classification of the Fear and Greed Index, Extreme Fear, Fear, Neutral, Greed, Extreme Greed.
btc_gt	Numeric	Google Trends score of search term "Bitcoin".

bert_pos_prob	Numeric	The probability of a positive sentiment label predicted by the BERT model.
bert_neg_prob	Numeric	The probability of a negative sentiment label predicted by the BERT model.
bert_label	Categorical	Sentiment label predicted by the BERT model, positive or negative.
finbert_pos_prob	Numeric	The probability of a positive sentiment label predicted by the FinBERT model.
finbert_neg_prob	Numeric	The probability of a negative sentiment label predicted by the FinBERT model.
finbert_label	Categorical	Sentiment label predicted by the FinBERT model, positive or negative.

3.4 Further Data Preprocessing

In this section, three feature engineering techniques are implemented for further preprocessing the data, One-Hot Encoding, Data Scaling, and Data Balancing. Each of these steps is essential for preparing the data for optimized machine learning performance and ensuring reduction of overfitting.

One-Hot Encoding: this technique is used for converting categorical variables into a binary or bool format. This is a widely used approach for encoding categorical features as machine learning algorithms can easily process one-hot encoded features. It transforms each category into a new binary column, where the occurrence of the category is marked by 1 and absence by 0. Here, categorical features, fng_class, bert_label, finbert_label, are one hot encoded for machine learning training.

Data Scaling: As skewness is present in the data, and numeric values ranges in different ranges, therefore, standardizing the numeric features is essential for optimizing model performance. This helps the model to reduce domination of high value features in model's prediction task.

Data Balancing: Here, the target variables, next_1d_movement, next_7d_movement, and next_30d_movement, contains imbalanced class distribution, meaning that some classes have significantly more samples compared to others. This kind of imbalance can lead the model to become biased towards the majority class and resulting poor prediction on the minority class. Therefore, Synthetic Minority Over-sampling Technique (SMOTE) is implemented for oversampling the minority class by interpolating between existing samples.

3.5 Model Training & Optimization

LSTM Model was trained on a series of experiments focusing on the prediction of price movements in different time frames, next day, next week and next month. Initially the data was split into 2 subsets, one containing BERT sentiment data and other containing FinBERT sentiment data, along with other sentiment and price data.

For each subset (BERT and FinBERT), the data was further split based on the target feature (next 1-day movement, next 7-day movement, and next 30-day movement). Each dataset had train test split ratio of 80% for training, 20% of testing, and the training set was further split a 20% portion for validation set.

The LSTM layers are configured with bidirectional layers, dropout layers and dense layers and optimized using RMSprop learning rate and categorical crossentropy.

Bidirectional LSTM Layers: This layer wraps the model with the number of memory cells and processes the input data for both forward and backward directions. This allows the model to capture complex patterns in sequential layers and learn from the previous layers. The model used 2 bidirectional layers with 64 and 32 LSTM units.

Dropout Layers: This layer ensures that the model does not rely on specific class during training in epochs and overfit. It randomly drops units from the training set at each epoch training. Here, 30% dropout rate was used during training the model.

Dense Layers: In this layer, ReLU (Rectified Linear Unit) activation function is applied, to help the model learn non-linear complex patterns. Further, L2 regularization technique is also for penalizing large weights to loss function with a purpose of reducing overfitting and achieving regularization.

Model Compilation: In optimizer argument, the model was set to a RMSprop learning rate of 0.001, which adapts the learning rate for each parameter and iteratively controls the step size while moving towards a minimum loss function. As it is a 3-class classification problem, categorical crossentropy function was applied in loss function.

3.6 Model Evaluation

Most studies used AUC and Accuracy to evaluate their model in classification problem. Thus, this study used the confusion matrix to evaluate the implemented model and AUC metric. The accuracy, Recall, F1-Score, and precision are obtained from the confusion matrix.

<table>
<tr><td></td><td colspan="4">Predicted Class</td></tr>
<tr><td rowspan="4">Actual Class</td><td></td><td>Class 0</td><td>Class 1</td><td>Class 2</td></tr>
<tr><td>Class 0</td><td>TP</td><td>FN</td><td>FN</td></tr>
<tr><td>Class 1</td><td>FP</td><td>TN</td><td>TN</td></tr>
<tr><td>Class 2</td><td>FP</td><td>TN</td><td>TN</td></tr>
</table>

Here,

TP = It shows the number of correct predictions on positive instances.

FP = It shows the number of incorrect predictions on positive instances.

FN = It shows the number of incorrect predictions on negative instances.

TN = It shows the number of correct predictions on negative instances.

Accuracy: Accuracy is the percentage of the total number of predictions that were correctly classified. The metric is calculated from the following equation

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}.$$

Precision: Precision is the proportion of the predicted true positive cases and is calculated from the equation

$$Precision = \frac{TP}{TP + FP}.$$

Recall: Recall is the proportion of positive cases that were correctly identified by the model. It focuses on the number of False Negative thrown into a prediction mixture. The recall is also known as sensitivity or true positive rate, and it is calculated as the following:

$$Recall = \frac{TP}{TP + FN}.$$

F1-Score: Precision or recall alone cannot describe the efficiency of a classier since good performance in one of those classes does not suggest good performance on the other class. For this reason, F1-Score, is considered as the most significant metric for evaluating classier performance. It is defined as the harmonic mean of precision and recall.

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall}.$$

The AUC evaluation metric is also used to measure the efficiency and performance of a binary Classifier. The AUC provides a more powerful evaluation metric than other evaluation metrics, which measures a supervised classification's overall performance by considering all potential cut-off points on the receiver's operating features curve.

CHAPTER - 4

RESULT ANALYSIS AND DISCUSSIONS

The LSTM model is trained on the 6 datasets separately containing 3 target features (next day, week and month price movement), with selected features by BERT and FinBERT sentiments and evaluated with 5-fold evaluation metrics on validation set. The model's performance on next day price movement prediction was not satisfactory, whereas next week and next month price movement prediction has shown significant accuracy and degree of generalization. Moreover, the model's consistent performance on validation set and test set shows its ability to generalize on unseen data. The model's performance on validation set and test set is shown below for each target prediction.

4.1 LSTM Model Performance on Next Day Price Movement Prediction

		Next Day Price Movement Prediction using BERT Features			
		Precision	Recall	F1 score	Support
Training Performance	0	0.52	0.71	0.60	4886
	1	0.66	0.70	0.68	4886
	2	0.80	0.47	0.59	4886
	Accuracy			**0.63**	14658
Test Performance	0	0.63	0.69	0.66	1222
	1	0.55	0.66	0.60	706
	2	0.69	0.43	0.53	700
	Accuracy			**0.61**	2628

		Next Day Price Movement Prediction using FinBERT Features			
		Precision	Recall	F1 score	Support
Training Performance	0	0.50	0.68	0.57	4886
	1	0.63	0.74	0.68	4886
	2	0.83	0.39	0.53	4886
	Accuracy			**0.60**	14658
Test Performance	0	0.62	0.67	0.64	1222
	1	0.53	0.73	0.61	706
	2	0.69	0.35	0.47	700
	Accuracy			**0.60**	2628

Table 4.1 Classification report of next day price movement prediction

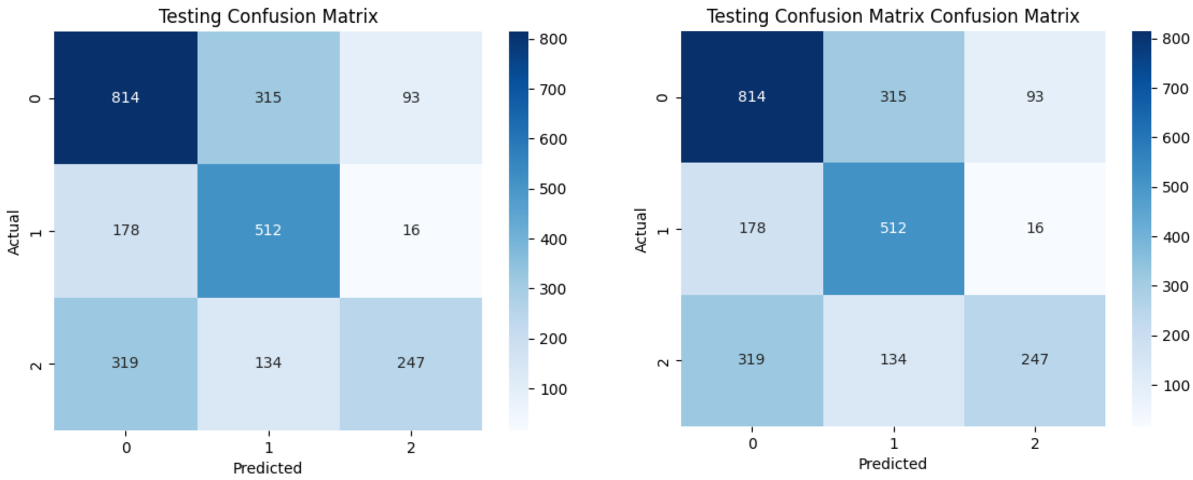

Figure 4.1 Confusion Matrix of next day price movement (BERT and FinBERT Features)

In predicting the next day price movement, the model's performance on BERT features achieved accuracy of 0.61, slightly higher than FinBERT features accuracy of 0.60. However, F1 score on BERT feature on class 2, 0.53, significantly outperforms the FinBERT features F1 score of 0.47. The confusion matrix and ROC curve here shows similar performance in both of the feature sets, indicating its inability to differentiate between BERT and FinBERT features. Moreover, indicating that FinBERT sentiments features are not providing the model greater prediction power.

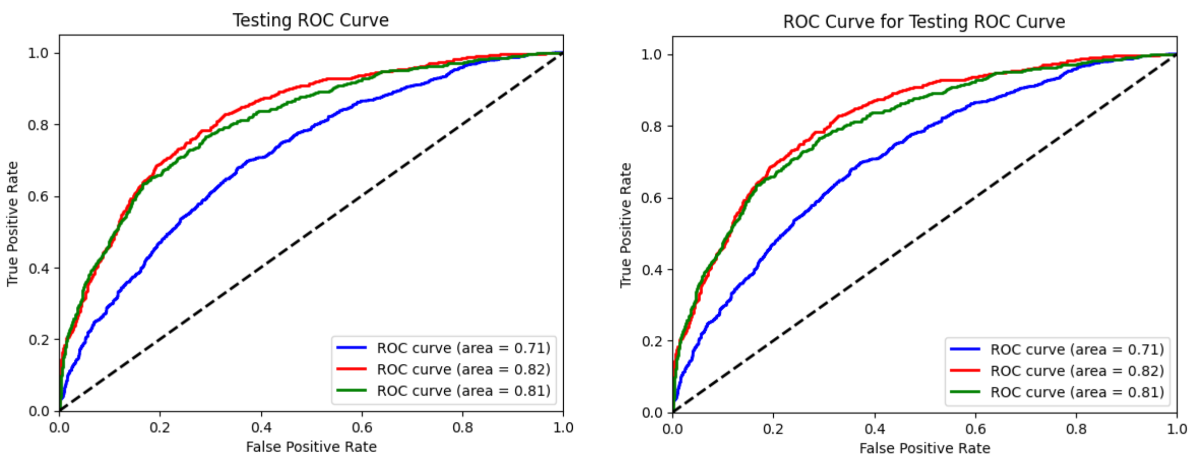

Figure 4.2 ROC Curve of next day price movement (BERT and FinBERT Features)

4.2 LSTM Model Performance on Next Week Price Movement Prediction

		Next Week Price Movement Prediction using BERT Features			
		Precision	Recall	F1 score	Support
Training Performance	0	0.80	0.87	0.83	4570
	1	0.90	0.89	0.90	4570
	2	0.94	0.87	0.91	4570
	Accuracy			**0.88**	13710
Test Performance	0	0.83	0.84	0.84	1142
	1	0.86	0.88	0.87	796
	2	0.88	0.84	0.86	690
	Accuracy			**0.85**	2628

		Next Week Price Movement Prediction using FinBERT Features			
		Precision	Recall	F1 score	Support
Training Performance	0	0.80	0.87	0.83	4570
	1	0.91	0.89	0.90	4570
	2	0.94	0.86	0.90	4570
	Accuracy			**0.88**	13710
Test Performance	0	0.84	0.86	0.85	1142
	1	0.88	0.88	0.88	796
	2	0.87	0.83	0.85	690
	Accuracy			**0.86**	2628

Table 4.2 Classification report on next week price movement prediction

In predicting the next week price movement, the LSTM model significantly improved its classification metrics on both BERT and FinBERT features with a similar performance on validation set. In the test performance on FinBERT features achieved accuracy of 0.86, slightly higher than BERT features accuracy of 0.85. Moreover, F1 score on FinBERT features are also a little ahead of BERT features.

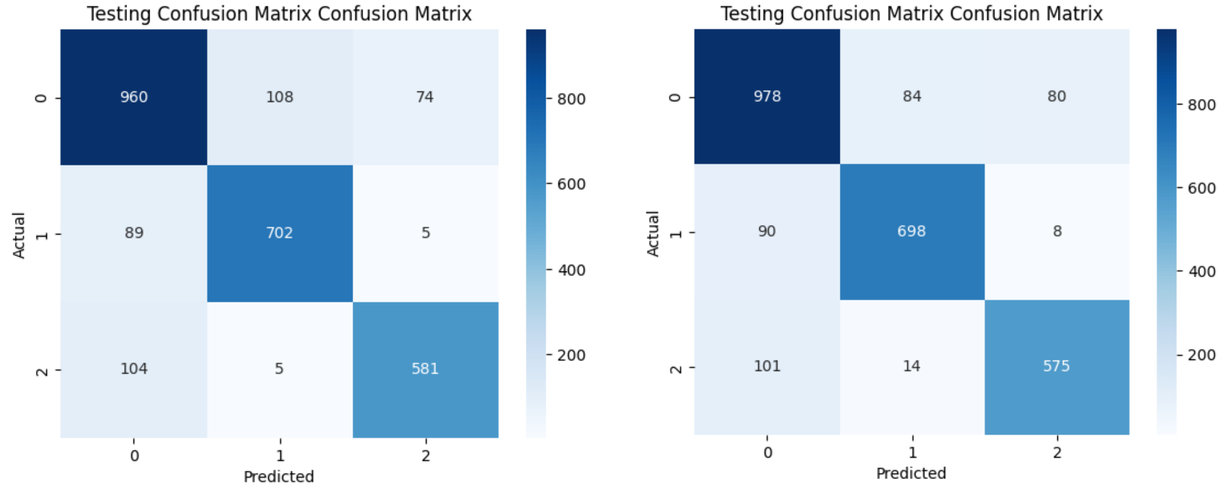

Figure 4.3 Confusion Matrix of next week price movement (BERT and FinBERT Features)

The confusion matrix and ROC curve here indicates the LSTM on FinBERT classifies class 0 better than LSTM on BERT. However, The BERT features allowed the model to predict class 1 and class 2 better than the FinBERT features. Moreover, the ROC curve shows similarity in both feature sets.

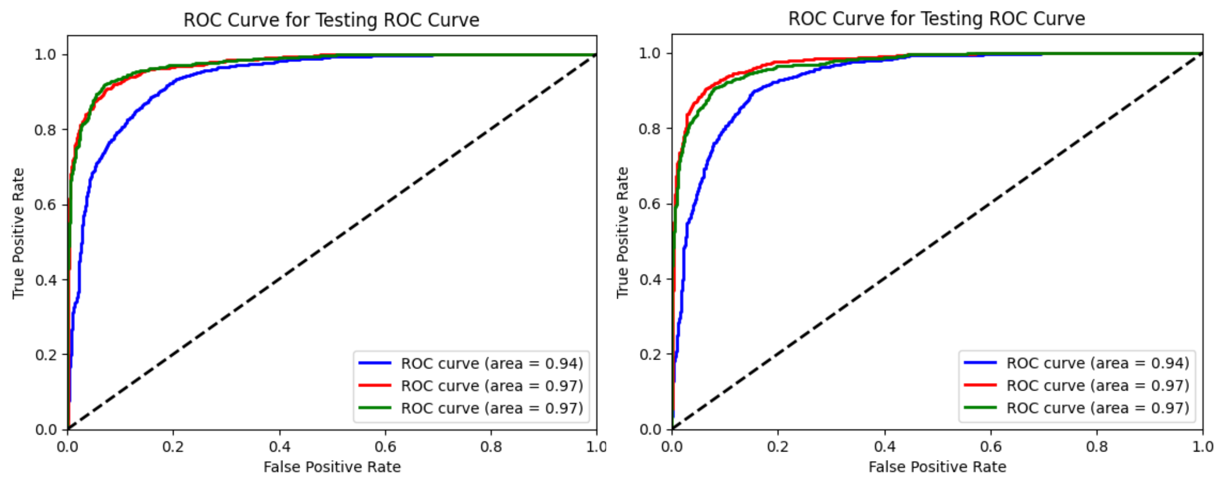

Figure 4.4 ROC Curve of next week price movement (BERT and FinBERT Features)

4.3 LSTM Model Performance on Next Month Price Movement Prediction

		Next Month Price Movement Prediction using BERT Features			
		Precision	Recall	F1 score	Support
Training Performance	0	0.92	0.92	0.92	3960
	1	0.95	0.96	0.96	3960
	2	0.97	0.96	0.96	3960
	Accuracy			**0.95**	11880
Test Performance	0	0.90	0.93	0.92	887
	1	0.96	0.95	0.96	990
	2	0.96	0.95	0.95	751
	Accuracy			**0.94**	2628

		Next Month Price Movement Prediction using FinBERT Features			
		Precision	Recall	F1 score	Support
Training Performance	0	0.92	0.92	0.92	3960
	1	0.95	0.95	0.95	3960
	2	0.96	0.96	0.96	3960
	Accuracy			**0.94**	11880
Test Performance	0	0.89	0.93	0.91	887
	1	0.96	0.94	0.95	990
	2	0.96	0.94	0.95	751
	Accuracy			**0.93**	2628

Table 4.3 Classification report of next month price movement prediction

In next month price movement prediction, the LSTM model on BERT regains it place from FinBERT in terms of classification metrics. The BERT feature set surges its accuracy to 0.95 on validation and 0.94 on test performance. The performance on FinBERT feature sets showed accuracy on validation set 0.94 and test set 0.93, which is slightly lower than BERT feature sets feature influence. Overall, LSTM on BERT features are comparatively ahead of LSTM on FinBERT features.

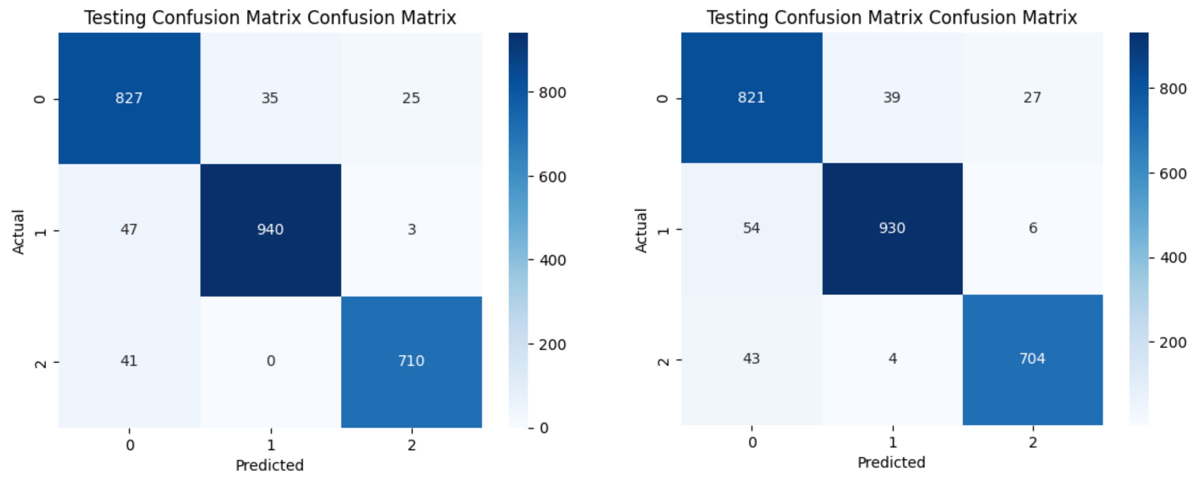

Figure 4.5Confusion Matrix of next month price movement (BERT and FinBERT Features)

The confusion matrix and ROC curve here indicates the LSTM on BERT classifies all classes better than LSTM on FinBERT. However, the ROC curve shows similarity in both feature sets. Moreover, there is no noticeable differentiation observed in using FinBERT features over BERT features while predicting price movements.

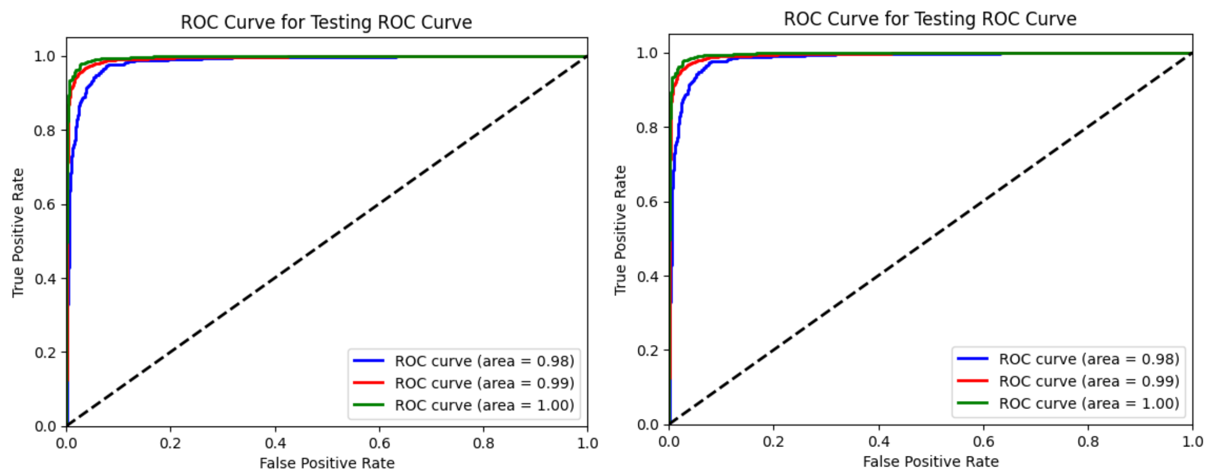

Figure 4.6 ROC Curve of next week price movement (BERT and FinBERT Features)

4.4 Discussion

The results from training the LSTM model on BERT and FinBERT feature sets, each containing three target features (next day, next week, and next month price movements), shows several insights into its predictive performance using BERT and FinBERT sentiment features.

Next Day Price Movement Prediction:

LSTM's performance on both of the feature sets generated similar performance suggesting that neither of the sentiment analysis model could provide significant predictive advantage for short-term (daily) price movements.

Next Week Price Movement Prediction:

The performance of LSTM model on BERT and FinBERT has significantly improved on predicting price movements on weekly price compared to daily price, indicating its ability to predict accurately over longer period price movements. However, no significant added advantage was observed in using FinBERT generated sentiment scores and labels over BERT sentiment scores and labels.

Next Month Price Movement Prediction:

The model's performance on next month price movement prediction has further improved as the time duration increased from week to month. This establishes that the model is suitable for mid-long-term price movement prediction rather that short-term price fluctuations.

Overall, the LSTM model illustrated strong generalization and better performance with FinBERT features for next week price predictions and BERT features for next month price predictions. However, the difference in performance metrics was very negligible. The absence of significant differentiation in using FinBERT over BERT suggests that for twitter sentiment analysis, FinBERT could not outperform BERT even though it is built for extracting sentiments in financial context. This may happen due to mixture of social contexts in tweets. Therefore, any of these models could be used for extracting sentiments from tweets and later on implemented on LSTM for weekly-monthly price movement prediction.

CHAPTER - 5
CONCLUSION

This primary objective of this research was to explore the influence of sentiment indicators, derived from twitter and other sources, on Bitcoin price movement. The main focus was to identify patterns on the price movement of bitcoin over different timeframe so that investors can be aware of whether they should make any investment decision based on these sentiments. For this purpose, this study used state-of-the-art deep learning models, BERT and FinBERT, to extract sentiments scores and labels from tweets related to bitcoin. Moreover, it included popular market indicator CFGI and google search trend data. Further, LSTM model was implemented separately on BERT and FinBERT feature sets, to unravel the influence of these sentiment scoring models on Bitcoin price movement over daily, weekly and monthly timeframes. The results of the analysis demonstrated strong generalization and performance of LSTM on FinBERT features for next week price movement predictions and BERT features for next month price direction predictions. However, there was no significant differentiation in using FinBERT over BERT, which suggested that for twitter sentiment analysis, FinBERT features could not add any additional predictive advantage over BERT features even though the model is built specifically for extracting sentiments in financial context, suggesting that either of these models could be used for extracting sentiments from tweets and later on implemented on LSTM for weekly-monthly price movement prediction.

Further work can be engaged on enhanced sentiment analysis using ensemble models combining BERT, FinBERT, and other appropriate models. Adding more features such as macroeconomic indicators, technical indicators, cryptocurrency news and articles, and on-chain metrics could improve the predictive power of the model and further identify key features influencing bitcoin price movement. Additionally, extended analysis on sentiment influence over other cryptocurrencies and financial markets may provide broader insight.

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