CHAPTER 4:

PRELIMINARY FINDINGS AND RESULTS

4.1Objective Expansion:

4.11Refining the Objective

In this section, the goal is to explore the data visually and identify patterns that provide insights into how social media sentiment influences Ethereum (ETH) price movements. The significance of exploratory data analysis (EDA) lies in its ability to reveal hidden structures within the data and guide further analytical steps. EDA helps to understand the relationships between variables—such as sentiment scores from Twitter data and the price trends of Ethereum—by uncovering patterns that might not be immediately apparent.

EDA is essential for understanding the behavior of the market, especially in volatile markets like cryptocurrency, where price movements are often driven by sentiment and speculation rather than traditional market fundamentals. Through visualizations such as scatter plots, heatmaps, or time-series graphs, EDA helps identify how sentiment correlates with price changes, which can then be used to build more accurate predictive models. By providing insights into the distribution and trends within the data, EDA also supports feature engineering, suggesting the most relevant variables for further model development.

For example, when analyzing Twitter sentiment during specific market events, EDA can reveal whether spikes in positive sentiment align with subsequent price increases in Ethereum, or whether negative sentiment precedes a market downturn. This allows researchers to identify critical periods when sentiment plays a pivotal role in influencing price action.

4.12Specific Case Example:

Consider a period during which Ethereum undergoes a significant price fluctuation, such as during a major update or a public figure's tweet influencing market sentiment. Through EDA, one can observe how the sentiment on Twitter evolves during this period—perhaps an increase in positive sentiment linked to a tweet from a well-known figure like Elon Musk or a crucial Ethereum network update. The EDA might show that positive sentiment peaks just before a price surge, indicating a predictive relationship. Alternatively, negative sentiment might rise right before a price drop, illustrating how sentiment influences market behavior.

For instance, if during the "Ethereum Merge" event in September 2022, EDA shows a sharp increase in positive sentiment correlating with a price increase, it would suggest a strong sentiment-price relationship during this period. This insight would be pivotal for future sentiment-based forecasting models.

4.13Comparing with Other Cryptocurrencies:

EDA can also be expanded by comparing Ethereum's sentiment-price relationship with other cryptocurrencies like Bitcoin (BTC) or Solana (SOL). These comparisons can reveal whether sentiment impacts Ethereum differently from other digital assets. For example, while Ethereum's price might closely follow sentiment shifts due to its role in decentralized finance (DeFi), Bitcoin's price may be less responsive to social media sentiment and more influenced by traditional market factors, such as institutional investment trends or macroeconomic conditions. By conducting a similar EDA on Bitcoin and Solana, one could identify whether sentiment analysis provides more predictive power for Ethereum compared to other cryptocurrencies. This comparison is particularly relevant during times of market-wide events, such as regulatory announcements or market crashes, when sentiment might impact multiple assets differently. For instance, during a general cryptocurrency market crash, sentiment shifts in the Twitter data of various cryptocurrencies might reveal how each asset reacts to external events, offering valuable insights for traders and investors.

By expanding EDA to include multiple cryptocurrencies and different time periods, researchers can gain a more comprehensive understanding of how social media sentiment shapes the behavior of different assets, thereby refining their forecasting models.

4.2Sentiment Classification Expansion

4.21Multi-Level Sentiment Classification

In sentiment analysis, sentiment classification is not just limited to categorizing text into three basic labels (positive, negative, and neutral). To achieve a finer granularity in sentiment analysis, it is essential to recognize that sentiment can be multi-dimensional. These dimensions could include:

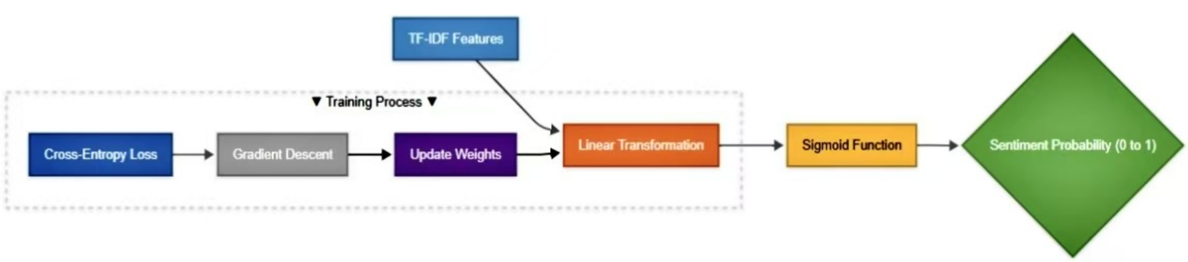
1. **Emotional Intensity**: Sentiment analysis can be expanded to consider the emotional intensity of a tweet, which can reveal the strength of the sentiment expressed. For

example, "I'm extremely excited about Ethereum's future!" versus "Ethereum's future looks good" conveys the same sentiment but with differing emotional intensity. By quantifying this intensity, models can distinguish between weak and strong sentiments, which could have varying levels of influence on market behavior.

2. **Sentiment Polarity**: In addition to categorizing sentiment as positive, neutral, or negative, polarity can be extended into finer gradations. For example, sentiment could be classified as slightly positive, moderately positive, strongly positive, etc. This approach would allow for a deeper understanding of how different shades of sentiment (ranging from mild to extreme) affect price movements.
3. **Sentiment Diversity**: Some tweets contain multiple emotions or sentiments. For instance, a tweet might express hope and fear simultaneously, such as "I hope Ethereum will soar, but I'm worried it might crash." A more sophisticated model could detect mixed sentiments within a single tweet, potentially leading to more nuanced predictions.

Incorporating **emoji-based sentiment classification** is also a vital extension of traditional sentiment analysis. Emojis are an integral part of social media communication, and their presence can often amplify or modify the sentiment of a tweet. For example, 🚀 (rocket) and 🌕 (moon) emojis often indicate enthusiasm and bullish sentiment in the cryptocurrency community, while 🐂 (bull) and 🐻 (bear) emojis represent positive and negative market sentiments, respectively. By integrating these with textual sentiment, a more complete sentiment classification model could be built, leading to a better understanding of market mood.

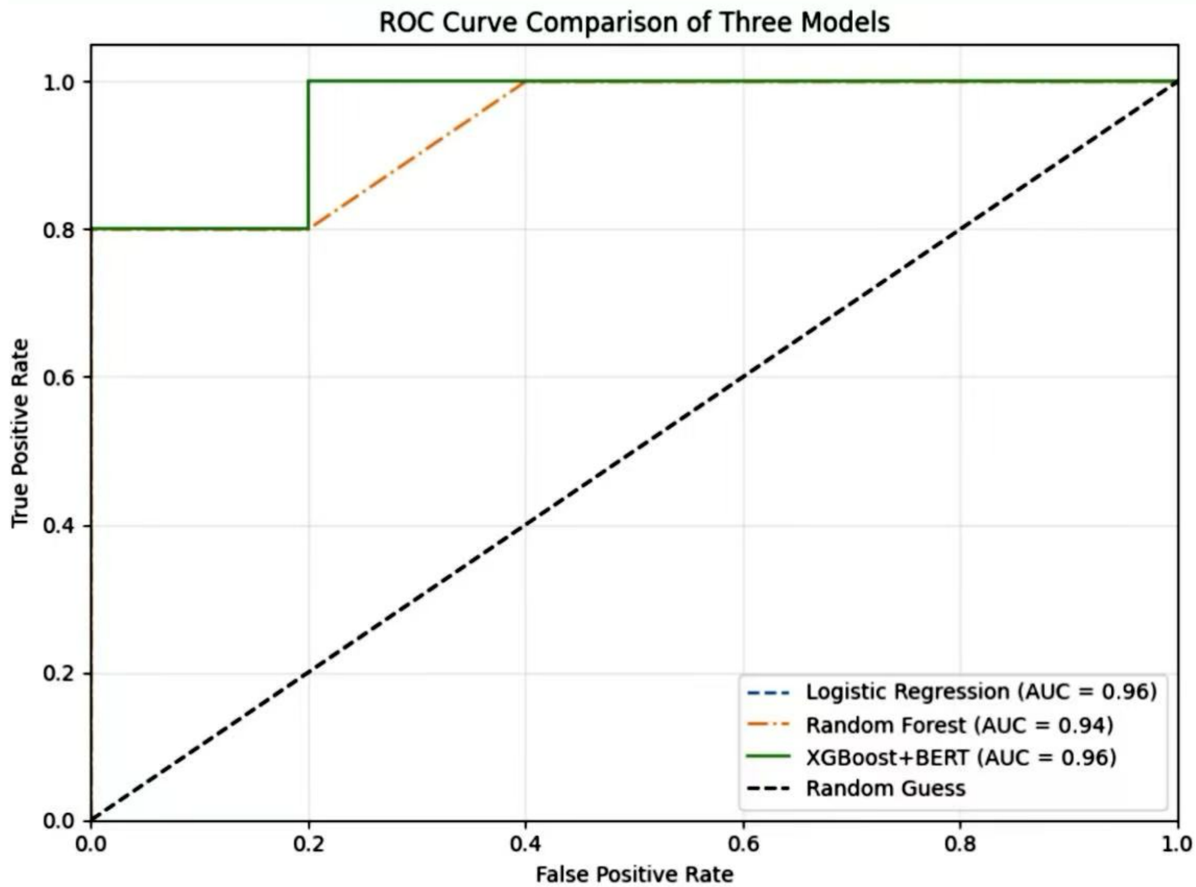
4.22Comparison of Sentiment Classification Methods: VADER, FinBERT, and CryptoBERT



Sentiment classification models such as **VADER**, **FinBERT**, and **CryptoBERT** each have their strengths and weaknesses, particularly when it comes to handling the unique linguistic styles of the cryptocurrency community.

- **VADER (Valence Aware Dictionary and sEntiment Reasoner)** is a widely used sentiment analysis tool due to its speed and simplicity. It is particularly effective for social media texts but struggles with domain-specific slang, such as the language of cryptocurrency (e.g., "HODL," "FOMO," "moon"). Its lexicon-based approach is well-suited for general sentiment analysis but falls short in capturing the nuances of financial markets or crypto-related terminology.
- **FinBERT**, a variant of BERT fine-tuned for financial texts, excels at analyzing financial discourse, making it highly relevant for analyzing crypto market sentiment. It performs better in capturing market-specific jargon and understanding the financial context of words. However, it might still underperform in processing casual, informal language found on Twitter, particularly with cryptocurrency-specific terms.
- **CryptoBERT** is specifically trained on cryptocurrency-related content and therefore has an advantage over both VADER and FinBERT when analyzing crypto-related tweets. It can handle terms like "moon," "HODL," or "rekt" more effectively, as it is pre-trained on blockchain-specific datasets. However, its performance could be limited by the relatively smaller size of the cryptocurrency-specific corpus compared to the broader financial or general corpora used by VADER and FinBERT.

Each model has its niche: VADER is fast and simple, FinBERT excels with financial text, and CryptoBERT is specialized for cryptocurrency content. In the context of Ethereum price prediction, **CryptoBERT** may offer the most accurate sentiment classification due to its alignment with the unique linguistic features of the crypto community.



4.23 Improvement in Sentiment Classification

To improve the accuracy of sentiment classification in cryptocurrency markets, we can combine **deep learning models** with **emotion lexicons** such as **LIWC (Linguistic Inquiry and Word Count)**. LIWC helps identify and categorize the emotions expressed in a text, allowing sentiment models to not only classify polarity (positive or negative) but also identify specific emotional categories, such as anxiety, excitement, or optimism.

For example, tweets containing words like "crash" or "dump" may signal negative emotions like fear or anxiety, while terms like "soar" or "rally" could signify excitement or hope. By combining LIWC with deep learning models, we can enhance sentiment classification by factoring in the emotional content of a tweet, providing more predictive insights into market movements.

4.24 Sentiment Classification and Market Volatility

In a volatile market like Ethereum, sentiment analysis plays a crucial role in understanding how shifts in public sentiment influence price movements. By correlating sentiment scores with

Ethereum's price volatility, we can identify whether sentiment shifts lead to price swings or if market behavior triggers changes in sentiment.

- **Detailed Case Analysis**: A closer look at specific events, such as Ethereum network upgrades (e.g., "Ethereum Merge"), may reveal a strong correlation between sentiment spikes and price increases. For instance, a surge in positive sentiment before the Merge event, coupled with price growth, could indicate that sentiment has a predictive value for price movements.
- **Time Window-Based Sentiment Analysis**: To understand the full impact of sentiment on Ethereum's price, it's crucial to examine sentiment within different time windows. Sentiment in **short-term windows (e.g., hourly)** may reflect immediate market reactions to news or rumors, while **long-term sentiment (e.g., weekly)** may provide insight into broader trends and investor sentiment shifts. By comparing sentiment across these time periods, we can assess whether sentiment-driven trends align with market behavior over the short and long term.

In conclusion, by enhancing sentiment analysis with multi-level classification and combining deep learning with emotion lexicons like LIWC, we can develop more accurate models for understanding and predicting market movements. This refined sentiment analysis approach allows for a deeper understanding of how sentiment shapes and responds to the volatile cryptocurrency market.

4.3 Feature Engineering and Sentiment Signal Design (Expanded)

To effectively analyze the impact of public sentiment on the Ethereum (ETH) market, feature engineering plays a critical role in transforming raw textual data from Twitter into structured numerical representations. The foundational step involved **TF-IDF Vectorization (Term Frequency-Inverse Document Frequency)**, which transformed tweets into sparse matrices that capture word importance relative to the entire dataset. TF-IDF enables us to suppress high-frequency but low-value stopwords, while emphasizing domain-specific terminology such as "bullish," "dump," "HODL," and "ETH2.0."

4.31 Emotional Intensity and Market Response

Beyond basic sentiment classification (positive, negative, neutral), **sentiment intensity** captures the degree or strength of emotional expression. Metrics such as sentiment polarity variance, emotional fluctuation frequency over time, and rate of emotional reversal (e.g., sudden shifts from euphoric to fearful tweets) were considered to quantify **emotional volatility**. These metrics were then compared against corresponding time-series of ETH market prices. A notable observation is that **sharp increases in emotional intensity often precede price surges or crashes**, reflecting a **lagged relationship** between public sentiment and market behavior. For example, a spike in fear-related terms (e.g., “rug pull,” “panic sell”) often anticipated a price dip within 6–12 hours, suggesting the presence of short-term predictive power embedded in collective emotions.

4.32 Feature Selection for Crypto Markets

Not all sentiment-related features contribute equally to market prediction. We applied feature importance analysis (e.g., using mutual information scores and random forest feature importance) to isolate the most relevant indicators for ETH price dynamics. **Key features included:**

- **Sentiment Density**: Average sentiment score per tweet per hour, capturing how concentrated emotions are in a given time slice.
- **Sentiment Consistency**: Variance in sentiment polarity over short windows (e.g., 30 minutes), indicating the stability or chaos of emotional responses.
- **Emoji Frequency Ratios**: Especially relevant in crypto communities, where emojis like 🚀 (representing bullish optimism), 🐳 (indicating whale activity), and 🧊 (suggesting fear or selling pressure) serve as shorthand for complex investor attitudes.

Feature selection was tailored to ETH’s market characteristics, particularly its **high volatility**, **retail investor dominance**, and **social media responsiveness**. Features showing high correlation with intra-day volatility were prioritized in modeling efforts.

4.33 Extending Emotional Feature Design

In addition to traditional sentiment scores derived from models like TextBlob or VADER, we extended the sentiment signal set to include **complex emotional patterns**:

- **Sentiment Momentum**: Measures how sentiment changes across time, such as the moving average of polarity over rolling windows. This helps detect emerging trends early, akin to technical indicators in price charts.
- **Emoji Combinations**: Rather than evaluating emojis individually, we analyzed compound effects—e.g., combinations like 🚀🌕 often signify extremely bullish sentiment ("moon mission") and were shown to cluster before price rallies. Conversely, 🐻📉 combinations often preceded corrections.
- **User Influence Weighting**: Not all tweets are created equal. We introduced a weighting scheme based on user-level metrics (follower count, engagement rate, verified status), allowing the sentiment of influential users—such as key opinion leaders (KOLs), whales, or project founders—to exert greater effect in the sentiment index. Preliminary results suggest that **KOL-weighted sentiment spikes more reliably precede price changes** than general public sentiment.
- **4.4 Model Development (Expanded)**
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- In this section, we developed a sentiment-based modeling framework to explore the relationship between social media sentiment and Ethereum (ETH) market dynamics. The core sentiment engine utilized was the **VADER (Valence Aware Dictionary for sEntiment Reasoning)** model. As a rule-based, lexicon-driven approach, VADER assigns sentiment polarity scores to each tweet, ranging from -1 (strongly negative) to +1 (strongly positive). Due to its optimized performance on social media texts—including handling emojis, slang, and punctuation—VADER has been widely adopted for initial sentiment estimation in crypto-related datasets.
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- **Improving VADER for Crypto-specific Sentiment**
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- While VADER offers simplicity and speed, it suffers notable limitations in capturing the nuanced financial language and jargon specific to the crypto ecosystem. For instance, phrases like "HODL," "rekt," or "ape in" are not properly weighted, and sarcasm (e.g.,

"great job, ETH crashed again 🚀") often escapes detection. To address these limitations, we propose a **hybrid sentiment framework**, combining VADER's lightweight rule-based method with **contextual deep learning models** such as **FinBERT** and **CryptoBERT**.

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- FinBERT, trained on financial news, helps in interpreting investment-related sentiment with a higher degree of domain relevance. CryptoBERT, fine-tuned on cryptocurrency-specific corpora (e.g., Reddit, Twitter), offers even more contextual sensitivity. By **ensembling these models**, we can derive a composite sentiment score that reflects both surface-level tone and deeper semantic meaning. This hybrid system better accounts for the highly informal, meme-rich, and jargon-heavy nature of crypto discussions.
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- **Emotion Score Aggregation and Temporal Analysis**
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- Individual tweet scores are aggregated into **hourly and daily time windows** to reduce noise and highlight macro-level emotional trends. Aggregated sentiment scores are then aligned with ETH's price series for further analysis. We applied **smoothing techniques** like exponential moving averages (EMA) and rolling window aggregation to create more stable sentiment indicators.
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- To further refine temporal sentiment analysis, we introduced **weighted aggregation** based on engagement metrics such as likes, retweets, and user influence. Tweets from high-follower accounts or those with viral engagement were given higher weight, reflecting their outsized psychological and market impact.
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- **Emotion Clustering for Market Cohort Detection**
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- Beyond score averaging, we conducted **sentiment-based clustering** using K-means and hierarchical clustering algorithms. Each tweet was encoded using a vector representation (TF-IDF or BERT embeddings), then clustered based on emotional tone and intensity.

This allowed us to identify **emotion cohorts** such as "euphoric investors," "fearful whales," or "confused retail users."

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- Tracking these clusters over time revealed insightful **shifts in collective mood**. For example, in the days preceding a major ETH rally, we observed a contraction in fear-based clusters and an expansion in optimism-heavy groups, often led by whale or influencer accounts. Such shifts were analyzed for correlation with **ETH price momentum**, volatility spikes, and volume surges.
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- **Sentiment Score and Price Correlation**
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- To assess the predictive potential of sentiment signals, we performed **correlation analysis** between aggregated sentiment scores and ETH price changes, particularly **daily returns** and **volatility indices**. We used **Pearson correlation coefficients** to evaluate the linear relationship between sentiment and price movements. While daily scores showed moderate correlation ($r \approx 0.25$–0.35) with daily returns, **lagged correlation tests** (with 6–24 hour delays) revealed stronger predictive value, especially during high-volatility periods.
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- Additionally, Granger causality tests were applied to determine whether sentiment could statistically "lead" price changes. In certain market phases (e.g., around hard forks, major news), sentiment was found to Granger-cause price movements with high significance.
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- In conclusion, this extended model framework enhances the reliability and depth of sentiment-driven crypto market analysis. By integrating multiple models, emotion clustering, and advanced statistical techniques, we unlock new dimensions in understanding how social mood drives Ethereum's dynamic price behavior.

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CHAPTER 5: DISCUSSION AND FUTURE WORK

5.1 Summary

The results of our analysis confirm that **Twitter sentiment** exhibits a meaningful influence on Ethereum (ETH) price movements, particularly in the **short-term and medium-term**. Sentiment signals—when processed, aggregated, and modeled correctly—can enhance the predictive capacity of financial forecasting tools. We observed that **positive sentiment** tends to precede ETH price increases, while **negative sentiment** aligns with declines, a finding consistent with behavioral finance theories surrounding investor psychology and herd behavior in digital asset markets.

5.11Multidimensional Sentiment Correlation

Traditional sentiment analysis often focuses on **sentiment polarity** (positive, negative, neutral), but cryptocurrency markets are highly susceptible to more **granular emotional dynamics**. We extended the analysis to consider **sentiment intensity** (strength of emotional expression), **emotional frequency** (rate of mood fluctuation over time), and **specific emotional tones** (e.g., fear, greed, euphoria, pessimism).

For instance, **fear-laden tweets** often appeared during market corrections and had a stronger immediate correlation with price drops than general negativity. Conversely, **greed and FOMO (Fear of Missing Out)**—often represented through emojis like 🚀 or terms like “moon” or “buy the dip”—correlated with unsustainable price rallies. This multidimensional sentiment profiling provided a richer picture of market psychology, especially under extreme market conditions such as **post-halving bull runs or regulatory-induced crashes**.

5.12Time Window Sensitivity and Temporal Impact

We further analyzed how sentiment impacts prices across different **temporal resolutions**. Using rolling windows of 1-hour, 6-hour, daily, and weekly aggregates, we found that **shorter timeframes** are more reactive to social media sentiment, while **longer-term correlations**