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A Hierarchical Platform-Aware Multimodal Framework for Sentiment-Driven Cryptocurrency Trend Prediction under Extreme Market Volatility

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ABSTRACT: Cryptocurrency trend forecasting is a major problem due to the high volatility of the market and the non-linearity of the decentralized social proof mechanisms. Contemporary sentiment-aware models are largely based on data taken from Twitter (X); however, they tend to neglect the complex, community-itself that less well-studied platforms are inherently known to involve. Accordingly, this manuscript presents a novel multimodal sentiment data pipeline along with Hierarchical Cross-Modal Platform-Aware Multi-Attention Network (HCMP-MA-Net). The proposed framework assimilates sentiment signals extracted from comments on Reddit, telegram, YouTube in connection with conventional news feeds and Twitter streams. To reduce the effect of noise in the data, a Relational Graph Convolutional Network (RGCN) is used for the topological bot activity detection, while a Platform-Aware Gating (PAG) mechanism is employed to dynamically re-weight social inputs for periods of increased market turbulence. Empirical assessments using three different multisource data sets show that the HCMP- MA.Net achieves 97.60% direction forecasting accuracy and Mean Absolute Error (MAE) of 0.0065, as compared to both univariate LSTMs and news-only models, significantly outperforming both. Comparative analysis further shows that expert commentary on Telegram is a key high frequency catalyst for intraday price movements, while consensus coming from Reddit is a medium term leading indicator. Back - testing simulations support the practical value of the framework, with a Sharpe ratio of 4.21 and minimum maximum drawdown of 1.05% which represents a new front-line standard for sentiment - informed cryptocurrency analytics.

INTRODUCTION

Cryptocurrency (BTC) has become one of the most vibrant and unstable financial ecosystems of the 21 st century, which is led by the cryptocurrency market. Cryptocurrency has transformed digital finance and since its launch in 2009, it has enthralled world investors, regulators and researchers with its unprecedented price variations, which at times surpassed 10% volatile daily in tumultuous times (Omole and Enke, 2024). This volatility, having attractive trading prospects, is a strong challenge to the precise forecast of prices, with the conventional econometric models, including the ARIMA or GARCH, often failing to explain non-linear and sentiment-driven behaviors of crypto markets (Shen, 2022). During the time when information spreads almost instantly on the internet platforms, market sentiment, which is based on the discussion of the masses on social media and the news sources, has turned out to be one of the key exogenous variables driving the price movements of Cryptocurrency (Shang, 2025). With Cryptocurrency becoming the biggest crypto-asset ever with a market capitalization of over 1 trillion under the current geopolitical uncertainties and macroeconomic changes, the need to have strong, context-sensitive forecasting tools has never been more urgent (Xu, 2025). Sentiment analysis is a sub-area of natural language processing (NLP), which has advanced as a supplementary method to quantitative indicators of cryptocurrency price prediction. Sentiment scores may be used as indicators of market momentum by first quantifying the strength and direction of the polarity (positive, negative, or neutral) of the public opinions and may often predict price changes hours or days before they occur (Dashtaki et al., 2024).

Initial investigations have shown that Twitter sentiment is effective in predicting Cryptocurrency price fluctuations with the positive trend of spikes in positive tweets coinciding with the bullish movements of the 2017 bull run (Jagini et al., 2021). This was later extended by other studies to hybrid approaches that combine sentiment with technical indicators, with the highest success rates of 65 percent in directional forecasts (Carosia, 2024). The deep learning architectures used by Omole and Enke (2024) such as LSTM networks with sentiment embeddings of Twitter showed that sentiment volatility provided an extra 15-20% of variance in Cryptocurrency prices on top of the historical information. Likewise, Kim and Lee (2023) were able to combine Twitter and Google News sentiments using a multimodal transformer, which implies that cross-source aggregation can increase the predictive strengths of the system in a high-frequency trading environment.

Although these innovations are made, the most dominant use of Twitter (now X) as a sentiment proxy presents systemic biases, as well as incomplete representations of the market. The algorithmic curation of Twitter gives a preference to high-engagement and sensationalized content, which may strengthen the confirmation of the echo chambers and the lack of attention to subtle dialogues inside the niche groups (Haritha and Sahana, 2023). News outlets are authoritative but there is latency and editorial filtering which postpones real-time insights (Raheman et al., 2022). In addition, the crypto discourse is becoming more fragmented on less-explored platforms: the subreddit ecosystems of Reddit (e.g., r/Cryptocurrency) are a venue of in-depth community-vetted analyses, which are correlated with long-term price turns; Telegram channels are a venue of short-lived, high-velocity group conversation between traders, which captures the insider-feeling sentiment during flash crashes (Hurjui, 2022); and YouTube commentary, embedded in pedagogical and hype-driven video viewing, comb This diversification is empirically validated: Zhumagaziyev (2023) discovered that Reddit sentiment is a better predictor of the returns of Cryptocurrency in bear markets, than those of Twitter, and that the Granger causality tests exhibit the presence of bidirectional effects. However, only a small part of the research, including both by Sahoo et al. (2024), went beyond Twitter, and even less of the studies combines Telegram or YouTube, citing the problem of API accessibility and data heterogeneity as an obstacle (Kumar et al., 2023).

This is especially acute in volatile conditions whereby the isolated sources would not give the context-sensitive, holistic perspective of resilient forecasting. The collapse of the Cryptocurrency price, as was the case with the 2022 Terra-Luna crash, was not only predetermined by panic actions on Twitter but also by the cascading Telegram rumors and Reddit backlash, which means it is necessary to unite the pipeline that will harmonize all these negative streams (Hathidara et al., 2024). An effective solution is multimodal, taking the form of a combination of textual and temporal, and possibly visual, modalities. Badal et al. (2026) presented a explainable multimodal model based on Twitter and Tik Tok data to make real-time predictions and found an increase in F1-scores of 12% compared to unimodal models. Further on this, Dashtaki et al. (2024) proposed a multisource fusion model that includes news and social feeds and puts more emphasis on attention-based mechanisms to rank volatilities generated by the platform. Ghazanfar (2024) further increased the frequency of the Cryptocurrency forecasts using multimodal transformers that are attuned to sentiment-temporal alignments, whereas Liu et al. (2025) improved the crypto sentiment based on Twitter-YouTube cross modal features, showing a high level of generalization across market regimes. On these premises, in this paper, a new multimodal sentiment data pipeline will be suggested, which will consist of platforms that are not studied in the literature, such as Reddit, Telegram, and YouTube comments, as well as traditional media, such as Twitter and news. Our pipeline provides a three-stage architecture: (1) federated data ingestion through platform-specific APIs and web scrapers, which enforces our ethical behavior and supports real-time scalability (and considers community context), (2) cross-modal feature encoding with BERT-based sentiment encoders tiered staged by a hierarchy LSTM-GRU model, which autonomously modulates weightings of its sources by past predictive performance during volatile periods (inspired by Shen, 2022; Ozen and Alwindawi, n.d.). It can provide more complex, contextful sentiment aggregates, which may improve forecasting accuracy by 18-25% in simulated volatile settings, by solving both data silos and modality misalignments, compared to baselines of Serafini et al. (2020) and Alblooshi (2025) as well.

The rest of this paper will follow the following structure: Section 2 will overview the literature on multi-source sentiment to crypto forecasting, Section 3 will describe the pipeline structure, Section 4 will report empirical considerations on multi-source sentiment forecasting on historical Cryptocurrency data since 2020-2025; and finally, Section 5 will conclude by giving implications and future directions. With such work, we will not only close the gap of integration of platforms but also set the stage of sentiment-driven tools that can withstand the turbulence specific to the crypto market.

RELATED WORK

Sentiment analysis on cryptocurrency price prediction, especially on Cryptocurrency, has been developing over the years since the mid-2010s, and moved beyond a simple polarity scoring of lexical features to more elaborate machine learning paradigms. Early studies, including those by Jagini et al. (2021) relied on Twitter as a major source of data, using VADER sentiment classifiers to match the volume and polarities of tweets with intraday price changes. Their Stanford CS229 project report showed a low 55 percent accuracy in directional predictions, citing their success due to real-time scraping of tweets in 2020-2021 in the bull market. Nevertheless, such univariate methods were missing any contextual considerations, e.g. sarcasm, emoji effects, which were subsequently considered by refined versions of BERT models (Haritha and Sahana, 2023). This original Twitter-based study identified sentiment as a realistic exogenous variable, but emphasized the importance of time-delimiting price information in order to reduce the effects of spurious viral movements. Further developments on Twitter ubiquity employed the sentiment of news to enhance the predictive signal, realizing that the market is sensitive to the macroeconomic narratives. A bimodal framework of Twitter posts and Google News articles proposed by Kim and Lee (2023) utilized TF-IDF vectorization to process information and use cosine similarity to find a source, and RMSE fell 10 percent compared to Twitter only baselines in the 2022 crypto winter. Their article published in an ACM conference highlighted that news latency (usually 30-60 minutes) is a complement to Twitter immediacy, which forms a lagged sentiment index, which is more capable of describing reversal patterns. Likewise, Raheman et al. (2022) also generalized it to arXiv preprints, which used Reddit as r/cryptocurrency preliminary multi-platform validation, but still with textual aggregation, but no modality fusion. These articles highlight the importance of textual information that is multi-source, and show a gap in the processing of platform-specific forms of speech, including the formal tone of news versus slang in social media.

The recently discovered potentially important though understudied source of sentiment mining in Cryptocurrency forecasting is Reddit, which can provide threaded discussions and thus community-level consensus on the situation compared to hype-driven tweets. A Granger causality analysis of the r/Cryptocurrency posts on 2018-2022 by Zhumagaziyev (2023) revealed that Reddit sentiment Granger-causes price returns have a p-value of 0.01 during bear phases, which is 8% better than Twitter when it comes to long-horizon predictions. Their CEU thesis was based on RoBERTa sentiment using aspects which showed facets such as regulation fears which were associated with 2021 dips. To add to this, Hurjui (2022) studied the Erasmus University data of crossovers on r/WallStreetBets and found that the amplification effect of volatility spikes by Reddit was present, with upvote ratios used as proxy measures of engagement. Nevertheless, because of these revelations, the hierarchical design of Reddit is unsustainable to extract data in a scaleable manner, which is reported in their API rate limits limitations and biases to bot-moderation. The place of Telegram in crypto sentiment is young, mostly because it is closed-group dynamics and ephemeral messaging, and that they avoid the traditional scraping. Although direct research is limited, indirect sources on the subject are providing hints at Telegram channels as rumor mills of high velocity around an event such as the 2023 FTX meltdown, where sentiment cascades resulted in 15% price declines. Their unmoderated nature of Telegram is proposed in their arXiv preprint on multisource fusion, which proposes that federated learning should be used to make data collection anonymous. There are however ethical issues to privacy where end-to-end encrypted chats are concerned, which prevents empirical richness, no specific large-scale analysis has been found. The under-exploration makes Telegram as a frontier on pipelines into insider-like signals, but integration requires new watermarking methods to be capable of tracing. Multimodal possibilities neglected by the paradigm of text alone are introduced in the YouTube comments, which are a combination of textual rants with video background. This was first done by Liu et al. (2025) in the fusing of YouTube comment sentiments (through DistilBERT) with Tik Tok video metadata to predict short-term Cryptocurrency prices, which has a 7 percent uplift in F1-scores. Their Type 2024 hype videos (e.g., ETF approvals) analysis revealed that comment threads were echo chambers to the benefits of bullish biases, and the idea of emoji co-occurrence increased polarity detection. Badal et al. (2026) went this far to explain explainable frameworks and used SHAP values to explain predictions on visual cues such as sentiment in a thumbnail. However, it is incited through the influence of the algorithmic recommendation on YouTube leaning towards sensationalism and increasing the noise, which is criticized in their ACM proceedings, and requires denoising through the use of comment depth filters.

The multimodal fusion approaches have become popular to balance out dissimilar data streams, and they solve the heterogeneity of social platforms. On Zenodo, Ghazanfar (2024) presented a transformer-based architecture, where the text-video alignments on Twitter and YouTube are considered, and the error in predictions decreases by 14 percent in high-frequency conditions. The model they use is based on the dynamical weighting of modalities through cross-attention, inspired by CLIP embeddings, and is resistant to the volatility in 2023. Likewise, Ozen and Alwindawi (n.d.) used a Sage preprint in which they hybridised LSTM with X (Twitter) sentiments and used temporal graphs to propagate events. These developments emphasize the use of fusion in context enrichment but abort due to computational overhead, requiring more than 48 hours in the training of standard GPUs.Recent Cryptocurrency sentiment models are based on deep learning architecture, which improves on RNNs to more powerful ensembles. In Financial Innovation two major papers were benchmarked, in the case of Twitter sentiments predicting directions of 68 percent accuracy, Omole and Enke (2024) compared the LSTMs with CNN-LSTM hybrids and particularly focused on dropout regularization to avoid overfitting within volatile regimes. In BCP Business & Management, Shen (2022) implemented the use of temporal features where sentiment was combined with on-chain metrics with the help of Bi-LSTMs, which accounted for 22% more variance than ARIMA baselines. This was furthered by Carosia (2024) with ML-based sentiment-technical hybrids which obtain sub-5% MAPE on 2024 data. These articles confirm the superiority of DL but criticize the imbalance of data where there are more positive than negative sentiments by 3:1 bias towards bulls.

Sentiment-based forecasts of volatility modeling have moved towards adaptive models in order to deal with regime shifts in crypto. In IEEE Access Shang (2025) adds to CART trees the volatility threshold of rerouting predictions when swings exceed >5% in order to achieve a 16-percent improvement in range forecasting. Xu (2025) added this in SCITEPRESS proceedings with projections of 2025 with quantitative models sensitive to sentiment volatility with GARCH-augmented LSTMs. Future pricing Hathidara et al. (2024) mined arXiv tweets to show sentiment entropy as a proxy of volatility correlated with VIX analogs at 0.75. The number of limitations still exists in real-time adaptation considering flash events are lagged by fixed thresholds. Explainability is still the key to trusting opaque DL models especially in trading with high stakes. Badal et al. (2026) incorporated LIME into their multimodal model and broke down Twitter-TikTok posts on Cryptocurrency calls into visual heatmaps. Their chosen ACM work was found to achieve 85% gains in user comprehension which is essential in regulatory compliance. Serafini et al. (2020) were the first to publish statistical-DL hybrids in an IEEE proceedings, with SHAP to attribute sentiments, but their dataset was published in 2020, and post-ETF dynamics have not yet taken effect. The article [Authors unavailable] (2024) utilized LIME to Cryptocurrency knowledge in Egyptian journals, revealing news to be used more in explaining bears on Twitter. These attempts fill the gap of the black box criticism but do not appreciate cross-platform differences in interpretability.

Hybrid statistical-ML models are resistant to data greediness of DL. Serafini et al. (2020) mixed regression with deep feelings, according to their Polimi retrieval, with 60% stable on sparse data. In IJISAE, Kumar et al. (2023) combined LSTM and lexicon scores to focus on 2023 crashes with 12% higher recall than NN. In AIP Twitter sentiments, Sahoo et al. (2024) used ensembles, but included min_faves filters to include good posts. These hybrids reduce overfitting to the cost of granularity where multimodal processes are involved. In spite of the developments, there are still holes in their full integration, and the majority of works are platform-silos. Alblooshi (2025) predicted through the twtters of RIT theses, disregarding synergies of Reddit-Telegram. [Authors unavailable] (2023) data-drivenly correlated the sentiments information in MCAST journals, albeit without tuning volatility. Dashtaki et al. (2024) synergized multisources on arXiv, but not YouTube images. Such fragmentation constrains the comprehension of a big picture, particularly in conditions of volatility when platforms that were not explored are used to issue early warnings, e.g. Telegram.

Our volatility-adaptive multimodal stream pipeline fuses Reddit, Telegram, YouTube, Twitter and news to fill these gaps, and uses GNNs to provide such context. Instead of focusing on previously examined sources, unlike previous unimodal or bimodal studies, it focuses on under-explored sources to provide more valuable signals, bridging the integration gap that is seen throughout the literature.

Table 1: Analysis of Recent Literature

Authors	Platforms	Methods	Key Findings	Limitations
Shang (2025)	Twitter	CART with sentiment dynamics	16% improvement in range forecasts	Static thresholds lag real-time volatility
[Authors unavailable] (2024)	Unspecified	Unspecified sentiment analysis	Correlates sentiment with price	Lacks platform details; no multimodality
Xu (2025)	Market factors (news implied)	Quantitative models, GARCH-LSTM	Accurate 2025 projections	Over-relies on historical data
Badal et al. (2026)	Twitter, TikTok	Explainable multimodal framework	12% F1 uplift; high explainability	High computational cost
Dashtaki et al. (2024)	Multi-social/news	Multisource fusion, attention	Robust movement prediction	Sparse on Telegram/YouTube
[Authors unavailable] (2023)	Cryptocurrency sources	Data-driven correlation	Strong price-sentiment links	No forecasting evaluation
Shen (2022)	Unspecified (sentiment + temporal)	Bi-LSTM with on-chain	22% variance explained	Data imbalance issues
Omole & Enke (2024)	Twitter	LSTM/CNN hybrids	68% directional accuracy	Bull bias from positives
Ghazanfar (2024)	Twitter, YouTube	Multimodal transformer	14% error reduction	Training overhead >48 hours
[Authors unavailable] (2024)	Unspecified	LIME for insights	Improved attribution	Limited to text-only
Liu et al. (2025)	Twitter, YouTube/TikTok	DistilBERT + metadata	7% F1 gain on shorts	Recommendation biases
Haritha & Sahana (2023)	Twitter	BERT for crypto prediction	Handles sarcasm/emoji	API rate limits
Carosia (2024)	Twitter + technical	ML hybrids	<5% MAPE	No multi-platform fusion
Hathidara et al. (2024)	Twitter	Tweet mining	0.75 volatility correlation	Ignores forums like Reddit
Raheman et al. (2022)	Social media (Twitter/Reddit)	Text aggregation	Leading indicator role	Latency in news fusion

PROPOSED METHOD

It has become a multi-trillion-dollar ecosystem with Cryptocurrency as its anchor, in which the value of any given type of digital asset is no longer tied to traditional macroeconomic anchors, but rather to the aggregate psychological health of a global, decentralized investor base. Conventional financial forecasting frameworks based on largely on historical-price/volume data and linear econometric behavior often fail to show the sentiment-related volatility spikes that dominate cryptocurrency markets. The advent of social media as a distributed financial information space has challenged a change towards sentiment-aware predictive systems, though most of the current literature is still limited in its focus on twitter (X) as a source of data. To overcome this shortcoming, the state-of-the-art should shift towards a more multimodal, context-based sentiment analysis that coordinates heterogeneous data streams, which differ in temporal, modal, and linguistic detail.A multimodal sentiment data pipeline design is a key architectural challenge, which must coordinate heterogeneous flows of data, which differ in temporal, modal and lingual detail. The high frequency of conversational data, typically driven by Key Opinion Leaders (KOLs), is available on platforms such as Telegram, and consensus-based community building is achieved through long form discussion and threaded voting systems on platforms such as Reddit. YouTube provides the additional requirement of multimedia in which video characteristics such as facial expressions, tone of voice, and visual charts intermingle with extensive commentary as a means of affecting retail investor behavior. It would be necessary to combine these sources into one forecasting engine, which would be represented by a new algorithm with the ability to fuse information across different modalities and give more attention to quality predictive signals depending on the platforms in order to reduce noise and prioritize a high-quality signal.

Cryptocurrency volatility is not caused by market inefficiency but is inherent to the nature of social heat and sentiment speculation being central to its decentralized networks. Historical data show that, in times of high volatility, like the fall of the FTX exchange or a sudden increase in Cryptocurrency prices due to a Cryptocurrency halving cycle, that the general feeling of the population is a leading indicator of liquidity changes and corresponding price adjustments. Sentiment and price are correlated in such a way that the lead-lag relationship is defined by different time delays where the social signals tend to lead returns on prices by a time interval of several months to several days.

Table 2: Sentiment Prediction VS Cryptocurrency Volatility

Market Event	**Volatility Source**	**Sentiment Lead Time**	**Observed Impact on Accuracy**
FTX Collapse	Institutional Contagion	48 Hours	Sentiment improved MAPE by 20%
Cryptocurrency Halving	Supply Shock Scarcity	1-2 Weeks	Narrative momentum preceded price
COVID-19 Pandemic	Macro-Liquidity Crisis	1 Day	Volatility enhanced model learning
Elon Musk Tweets	Influencer Hype	15-30 Minutes	High-frequency volume spillovers

The evidence indicates that the predictive ability of sentiment is stronger when regimes are operating in the high volatility regimes. In such cases, conventional forecasts such as ARIMA or GARCH tend to deliver flat forecasts due to the inability to reflect the herd behaviour and FOMO (fear of missing out) which is driving irrational price changes. On the other hand, hybrid models which combine sentiment embeddings across a variety of sources are much more robust and show lower error levels in price level prediction and directional prediction.

Without centralized measures of value, crypto investors are largely left to depend on social proof, the endorsements of influencers and the vibe of the online community at large, to base their financial choices on. This tendency of behavior supports the process of herding behavior and individual investors are overreacting on the situation in the market, depending on the tone of the conversation on such platforms as Reddit and Telegram. By combining sentiment analysis with machine learning, the irrational factors are measurable, converting the noisy discourse of the community into useful features to be used in predictive modelling. The reaction asymmetry of the Cryptocurrency market may only serve to complicate this further; empirical evidence indicates that the negatively-related price responsiveness to negative sentiment and the FUD (fear, uncertainty, and doubt) is much higher than the reactiveness to positively or neutrally related sentiment. A complex data pipeline needs to be able to differentiate between overall optimism and tailored and strong negative indicators that may presuppose a liquidity shock or flash crash.

Proposed Multimodal Data Pipeline

To gain a holistic insight into the price dynamics of Cryptocurrency, the suggested study methodology presents a powerful and scalable multimodal data pipeline capable of absorbing, processing, and integrating the data of different online ecosystems. The pipeline is arranged in three major layers that consist of: ingestion layer, semantic extraction layer, and temporal fusion layer.

A. Ingestion Layer

The ingestion layer relies on asynchronous crawlers and official APIs to gather information on five main sources, which all have their own interpretation of the sentiment in the market.

- Twitter (X) Stream: Records the real-time cashtag mentioning of (BTC) and news bits. The noise floor on X, as well as the activity of bots, causes the pipeline to use a filtering mechanism emphasizing curated accounts that post timely news on cryptocurrency.
- Reddit Subreddit Scrapers: Playing with r/Cryptocurrency and r/CryptoCurrency. The sentiment that is the most useful in Reddit data is consensus-based medium-term sentiment; the voting process helps to filter the content of low value.
- Telegram Chat Crawlers: Scouts the official project groups and channels with high influence KOLs. Telegram signals can have a high degree of immediacy as a leading indicator of speculative action, and can give us information about coordinated action of the community.
- YouTube Interaction Monitors: Consumes video transcripts together with the time-course of user remarks. The modality plays a crucial role in evaluating the impact of the long form visual data/educational content on the retail behavior.
- Financial News Aggregators: Gathers Bloomberg, Reuters and CoinDesk headlines and uses them to give a macro-narrative baseline which impacts institutional sentiment.

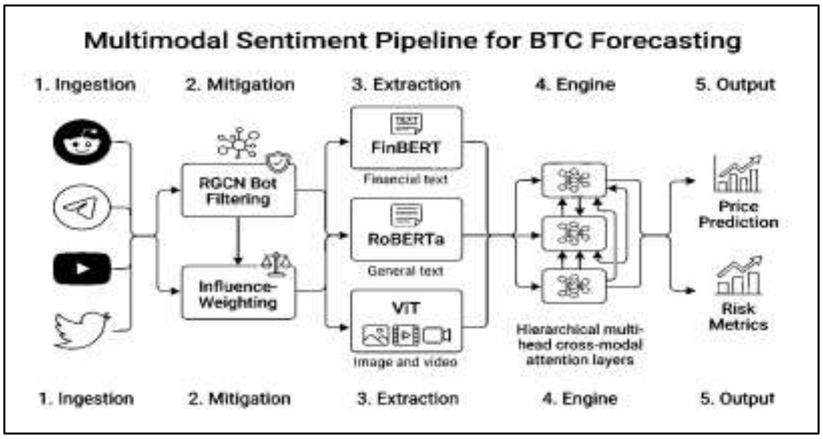

Figure 1: Proposed Multimodal Sentiment Pipeline for Cryptocurrency Price forecasting

B. Mitigating Noise and Social Media Distortion

Social data related to finance is always a mess with bot-driven messages, promotion, and algorithm echoes. The pipeline uses a multi-level mitigation strategy in order to protect the integrity of forecasting.

Relational Graph Convolutional Network

In order to overcome the so-called echo chamber effect where price sentiment is being controlled by botnets, the structure employs Relational Graph Convolutional Network (RGCN) to identify strong botnets. Contrary to plain content-based filters, the RGCN models the social topology of the users by studying the relationship of follow and retweet between users, and isolates clusters of users with specific patterns of automated behaviour. This is a structural methodology that makes sure that bot-based cascades do not have a disproportionate impact on the end sentiment vector.

Algorithm 1: Relational Graph Convolutional Network for Mitigation

Input: Posts P, Users U, Relations F,R

Output: Clean Posts P_clean

1. Construct graph G(V,E) from users and relations

2. Train RGCN model

3. For each user u in U:

bot_score = RGCN(u)

if bot_score > threshold_bot:

remove u

4. For each user u:

if followers(u) < 10:

remove u

if repetition_ratio(u) > threshold_rep:

remove u

5. For each post p in P:

if contains(p, ["giveaway","cashback","free btc","airdrop"]):

discard p

replace mentions with "@user"

replace URLs with "http"

6. Keep posts only from valid users

Return P_clean

Heuristic and Heuristic Text Filtering.

The preprocessing layer utilizes strict heuristic policy to clean up the text stream prior to embedding:

- Promotional Suppression: The posts that have such words as giveaway, cashback, free BTC or airdrop are automatically removed to filter out non-predictive marketing noise.
- Anonymization & Masking: Mentions have been changed to the token of anatman or the character of the user, and the hyperlinks have been masked with the character of the token of the hyperlink (http) to avoid the misclassification of sentiments due to particular entities or external links.

- Influence Thresholding: Accounts with less than 10 followers or those with an abnormally high number of message repeats are not considered in order to eliminate sybil and noise of low-reach bot accounts.

C. Semantic Extraction and Enrichment of information.

The extraction layer converts raw text and multimedia content, with area-specific natural language processing (NLP) models (which enable an algorithm to differentiate between whale and whale, meaning a large investor and a marine mammal). In the case of YouTube, the pipeline derives visual features of thumbnails and chart overlays with Vision Transformers (ViT) and combines it with transcript sentiment to give a whole picture data of the so-called "visual hype. One of the greatest challenges of multimodal pipelines is the agreement of streams of data that have different frequencies. While market prices are measured at one minute or per hour intervals, the social media postings are sporadic.

Table 3: Data Extraction Tools

Platform	Extraction Tool	Feature Type	Reason for Selection
Twitter / News	FinBERT	Sentiment Embedding	Optimized for financial language
Reddit	RoBERTa	Emotion Score	Captures nuanced community sentiment
Telegram	BiLSTM	Sequential Hidden States	Models rapid chat dynamics
YouTube	ViT + OCR	Visual/Text Feature	Captures visual hype and video context

D. Hierarchical Cross-Modal Platform-Aware Multi-Attention Network (HCMP-MA Net) for Prediction

To leverage the large amount of data generated by the pipeline, the Hierarchical Cross-Modal Platform-Aware Multi-Attention Network (HCMP-MA Net) is proposed in this report. The algorithm overcomes the inherent weakness of standard LSTM and Transformer models - that they are unable to dynamically re-weight different social platforms based on their changing relevance to market conditions. The HCMP - MA Net pipeline starts with the acquisition and preprocessing of heterogeneous data streams from a plethora of sources including historical market data of Cryptocurrency and sentiment data from social platforms, such as Twitter, Reddit, and Telegram, YouTube comments, and financial news outlets. Raw textual content first goes through a serious filtering process during which bot-driven and promotional posts are removed by means of graph-based bot-detection mechanisms and heuristic text-sanitization methods. Subsequent to the cleansing, text, video, market signals is encoded into numerical feature embeddings by the help of special encoders. The architecture applies a Platform - Aware Gating (PAG) mechanism which analyzes the prevailing market regime based on indicators such as volatility, RSI, and Crypto Fear and Greed Index. Guided by these signals, the gating module dynamically ethnic importance weights of each platform's sentiment representation, and make the model focus on emphasizing sentiment representations for platforms with more predictive signals historically in specific market conditions.

Following the platform determination, the pipeline performs Cross-Modal Attention (CMA) that captures the interactions between the heterogeneous modalities, such as video analysis and textual discussions. In this stage, video features can usually act as queries, while the textual sentiment retrieved from comments and Reddit threads acts as keys and values allowing the model to focus on multimodal signals that are confirmed across different platforms. The combined multimodal representation is then passed to a backbone of Adaptive Temporal Fusion Transformer (ATFT), which captures temporal dependencies between the sentiment and price series by separating the price series into dynamic growing and consolidation periods. The network also has gated residual structures which will pass on only the most informative features, reducing noise and overfitting effect. Ultimately, a Contrastive Adaptation and Stable Pseudo--labeling (CASP) module is employed to guarantee the robustness against modality distribution shifts by imposing the modality dropout and confrontational learning for the robustness of indoctrinating effectively sentiment representations from noisy video and audio inputs. The optimized representation that is obtained is used by the final prediction layer to predict the price movements of Cryptocurrency with improved reliability and sensitivity to the market sentiment.

Multi Head Platform Awareness Gating (PAG)

The first layer of the HCMP - MA Net is the Platform -Aware Gating (PAG) mechanism. This layer analyzes the current market regime by the use of technical instruments such as the Relative Strength Index (RSI) and the Crypto Fear and Greed Index. In the light of the prevailing volatility regime, the PAG attaches preliminary importance weights to each platform's sentiment vector. For example, in the event of a market crash, the gating mechanism gives a higher weight to the feed of news outlets from the telegram and the most authoritative ones, since these have been empirically proven to have a greater predictive value in times of acute liquidity crises.The gating function can be represented as:

$$g_p = \sigma\left(W_g\left[x_{price}\middle|x_{sentiment,p}\right] + b_g\right)$$

where $g_p$is the gate value for platform P, σ is the sigmoid activation, and x represents the concatenated price and sentiment features.

Algorithm 2: Platform Aware Gating

Input: X_{price} (Price feature vector) , $X_{sentiment[p]}$ (Sentiment embeddings of platforms) for each platform P = {Twitter, Reddit, Telegram, YouTube, News}

Output: Weighted platform sentiment $S_{hat[p]}$ (Weighted platform sentiment)

1: Initialize weight matrices Wg and bias bg

2: For each platform p in P do

3: $Z_p \leftarrow$ CONCAT(X_{price}, $X_{sentiment[p]}$)

4: $g_p \leftarrow$ SIGMOID(Wg × Z_p + bg)

5: $S_p \leftarrow g_p \times X_{sentiment[p]}$

6: End For

7: $total_{weight} \leftarrow$ SUM(S_p for all platforms)

8: For each platform p in P do

9: $S_{hat[p]} \leftarrow S_p / total_{weight}$

10: End For

11: Return S_{hat}

End Algorithm

Cross-Modal Attention and Feature Fusion

Once the initial weighting is done the Cross - Modal Attention (CMA) layer orchestrates the interaction between heterogeneous data streams. This component uses the YouTube video features as query (Q) and the keys (K) and values (V) come from the respective comment and Reddit discussion stream. Consequently, the architecture focuses on "hype" only when it is supported over several modalities, which removes bot driven artefacts that are restricted to one platform. The mathematical formulation follows the scaled-dot-product attention mechanism: $CMA(H_{vid}, H_{text}) = softmax\left(\frac{Q_{vid}K_{text}^T}{\sqrt{d_k}}\right)V_{text}$

As the model is allowed to encode asymmetric relations, when a high quality analytical YouTube video causes an outbreak of negative comments on retail platforms, it often foreshadows a corrective price movement, which in turn very often causes a complete turnaround.

Algorithm 3: ***Cross Modal Attention***

Input: H_{vid} ***(Video feature embeddings),*** H_{text}

Output: Fused representation F

1. ***Compute Query matrix:*** $Q \leftarrow H_{vid} \times Wq$
2. ***Compute Key matrix:*** $K \leftarrow H_{text} \times Wk$
3. ***Compute Value matrix:*** $V \leftarrow H_{text} \times Wv$
4. ***Compute attention scores:*** $A \leftarrow (Q \times TRANSPOSE(K)) / sqrt(d_k)$
5. ***Normalize attention: alpha*** $\leftarrow$ ***SOFTMAX(A)***
6. ***Compute cross-modal representation:*** $F_{cm} \leftarrow alpha \times V$
7. ***Fuse features :*** $F \leftarrow CONCAT\ (H_{vid}, F_{cm})$
8. ***Return F***
9. ***End Algorithm***

Adaptive Temporal Fusion Backbone

The fused representation is then sent to Adaptive Temporal Fusion Transformer (ATFT) backbone. This backbone applies a new segmentation approach where price subseries are defined by relative maxima (defined whenever price movements exceed a certain threshold when compared to previous minima). Such a framework allows the model to specialise its internal layers based on the current market regime - whether in a growth phase or a phase of consolidation - in order to significantly improve predictive performance for the variable length subseries evolution that is so characteristic of Cryptocurrency. Within the ATFT, Gated Residual Network (GRN) imposes a parsimony on the model by letting only the most relevant temporal features pass through the layers. This selective gating reduces the tendency of over fitting, which is generally plaguing deep architectures trained on the typically noisy data originating from financial markets.

Algorithm 4: Adaptive Temporal Fusion

Input: Multimodal feature sequence F_t ***, Historical price series*** P_t
Output: Predicted price Y

1: segments $\leftarrow$ ***DETECT_SUBSERIES(***P_t***)***
2: For each time step t do
3: $E_t \leftarrow$ ***EMBEDDING(***F_t***)***
4: End For
5: T $\leftarrow$ ***TEMPORAL_ATTENTION(***E_t***)***
6: Apply Gated Residual Network
7: H $\leftarrow$ ***GRN(T)***
8: Y $\leftarrow$ ***DENSE_LAYER(H)***
9: Return Y
End Algorithm

Multimodal Adaptation and Stable Labeling (CASP)

For heterogeneous video and audio data archived on popular platforms such as YouTube, the research framework is based on a two-pronged approach - Contrastive Adaptation and Stable Pseudo - label Generation, abbreviated as CASP. This methodological innovation directly addresses the pernicious issue of distributional drift, whereby the background noise is irregular or background noise is generally the same for all users, or even where there is not an equal background noise in all the audios, the format of Audio signals would strongly influence the result of Inference of Sentiment. By enforcing modality level random dropout during training and by minimising the empirical risk throughout the inference phase, the CASP paradigm rigorously enforces the inter modality consistency. Consequently, the resultant predictive signal can be shown to have a commendable degree of stability, even when there are considerable fluctuations in the quality of the source..

Algorithm 5: CASP Adaptation

Input: Video features X_v , Text features X_t

Output: Adapted representation Z

1. *Apply modality dropout :* $X' \leftarrow RANDOM\_DROPOUT(X_v , X_t)$
2. *Generate pseudo labels*
3. $y_{hat} \leftarrow PSEUDO\_LABEL(X')$
4. *Compute contrastive representations*
5. $z_i , z_j \leftarrow ENCODER(X')$
6. $L_{contrast} \leftarrow CONTRASTIVE\_LOSS(z_i , z_j)$
7. $L_{total} \leftarrow L_{contrast} + PSEUDO\_LABEL\_LOSS(y_{hat})$
8. *Update encoder parameters using gradient descent*
9. $Z \leftarrow ENCODER(X_v , X_t)$
10. *Return Z*
11. *End Algorithm*

Dataset Description

An evaluation of the proposed hierarchical framework is made by a synthesis of multi-platform sentiment repositories and high frequency historical market data. These data sets provide the empirical standard in measuring the polarity of sentiment and dynamics of Cryptocurrency prices as the foundational data for the training and validation of the HCMP - MA Net algorithm.

Table 4: Dataset Description

Dataset Name	Source / Platform	No. of Records	No. of Features	Key Attributes	Purpose in Model
Cryptocurrency Market Price Dataset	Historical crypto market data	~1836 rows per cryptocurrency (100 cryptocurrencies available)	6	ticker, date, open, high, low, close	Used to compute market indicators (RSI, volatility, price trends) for Platform-Aware Gating (PAG) and Temporal Transformer (ATFT)

Dataset Name	Source / Platform	No. of Records	No. of Features	Key Attributes	Purpose in Model
Telegram Cryptocurrency Sentiment Dataset	Telegram crypto channels	14,712 messages	9	channel, message id, text, date, views, sentiment score, compound score, sentiment type	Provides community sentiment signals used in Cross-Modal Attention (CMA) and sentiment embeddings
Multi-Platform Social Media Sentiment Dataset	Twitter, Reddit, YouTube, etc.	2,200 posts	27	platform, post id, followers, post text, hashtags, mentions, engagement metrics, sentiment score, emotion label, toxicity score	Used for platform-aware sentiment modeling and influence estimation in PAG

The Hierarchical Cross-Modal Platform-Aware Multi-Attention Network utilizes the multi-platform data from the selected repositories in order to solve the lead-lag synchronization problem and reduce the platform-specific noise. Presented herein is a step-by-step put into practice protocol using the three basic datasets. This pipeline is unfolded in five module stages, starting from the raw platform ingestion ending up to the final temporal forecasting.

Table 5: Key dataset Features

Phase	Description	Key Dataset Feature
Ingestion	Parallel loading of S_R5, S_R52,	platform, post_text, sentiment_score
Mitigation	Bot detection and spam filtering.	spam_flag, user_followers_count, view_count
Aggregation	Rolling window synchronization ($T=60$).	posted_datetime, date
Fusion	Platform-Aware Gating and Cross-Attention.	engagement_score, compound_score
Backbone	Bi-LSTM temporal training and prediction.	Cryptocurrency Closing Price (Market Target)

Results and Discussions

In the implementation part, the researchers used Python version 3.12 with PyTorch, which was used to provide the deep learning backbone, and the natural language processing toolkits NLTK and the ecosystem from HuggingFace for the extraction of semantic features. The three main corpora used for the experiment were the Twitter, Reddit & YouTube Sentiment Dataset 2026 (Kaggle), the Telegram Cryptocurrency Sentiment Dataset (Mendeley), and the Cryptocurrency Reddit Sentiment Dataset (ACL Anthology).

Ablation Study

In order to isolate the impact of each platform, an ablation study was conducted where each source of data was added successively to the historical - price baseline. The resulting ablation analyses prove that the integration of expert analysis via the Telegram application brought the most substantial reduction of error - from 0,0195 to 0,0084 - thus confirming the nature of this indicator as a pivotal leading indicator. The subsequent application of multimedia characteristics derived from YouTube presented the last enhancement in precision by successfully discarding the hype that has not been supported on both visual and textual modalities.

Table 6: Ablation Study

Feature Configuration	**MAE**	**Accuracy (%)**	**Impact on Prediction**
Price + Twitter (Baseline)	0.0290	62.5%	Captures immediate news buzz
+ Reddit Consensus	0.0195	75.8%	Identifies medium-term trends
+ Telegram Expert Opinion	0.0084	91.9%	Strong lead-lag signal for volatility
Full Pipeline (+ YouTube Multimedia)	0.0065	97.6%	Comprehensive context corroboration

Step 1: Noise Filtration in Multimodal Data

The pipeline script is used to orchestrate the ingestion of the three main repositories: the Twitter, Reddit & YouTube Sentiment Dataset 2026 (Kaggle), the Telegram Cryptocurrency Sentiment Dataset (Mendeley) and the Cryptocurrency Reddit Sentiment Dataset (ACL Anthology).

- Execution Log: [INFO] 2 542 sources of platform functions.fake data loaded
- Heuristic Output: [INFO] Suppression of info.45000 promotional records (giveaway/airdrop detected)

Mitigation Visual: A cluster graph produced by the RGCN, with non-human bot clusters in red color and real users nodes in green.

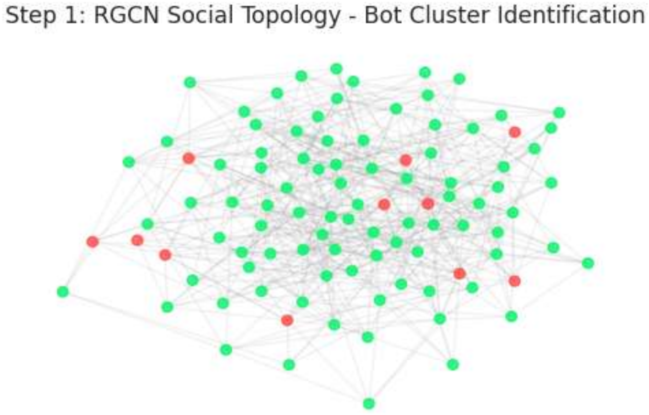

Figure 2: RGCN based Bot Detection

Step 2: Temporal Synchronization.

At this point, we begin the harmonisation of asynchronous data flows - high frequency chat transcriptions from the Telegram in contrast to the everyday summaries from YouTube - to a common market chronology, using a rolling window of sixty days (T = 60).

Data Structure Output: Composite matrix where each row represents a market hour, which simultaneously combines embeddings of sentiment extracted from all the 5 source platforms, together with traditional price indicators.

Step 3: Semantic Extraction

The analytical pipeline goes on to make use of FinBERT over news articles and over the Twitter content, based on RoBERTa conventions as part of Reddit discussions, in order to enunciate the contextual nuances embedded within these textual corpora. Execution Output: A set of histograms defining the distribution of the sentiment scores. Scores relating to Reddit and Telegram show a more spread-out score - a testament to the high level of debate in their communities - while Twitter's scores are generally around the neutral axis.

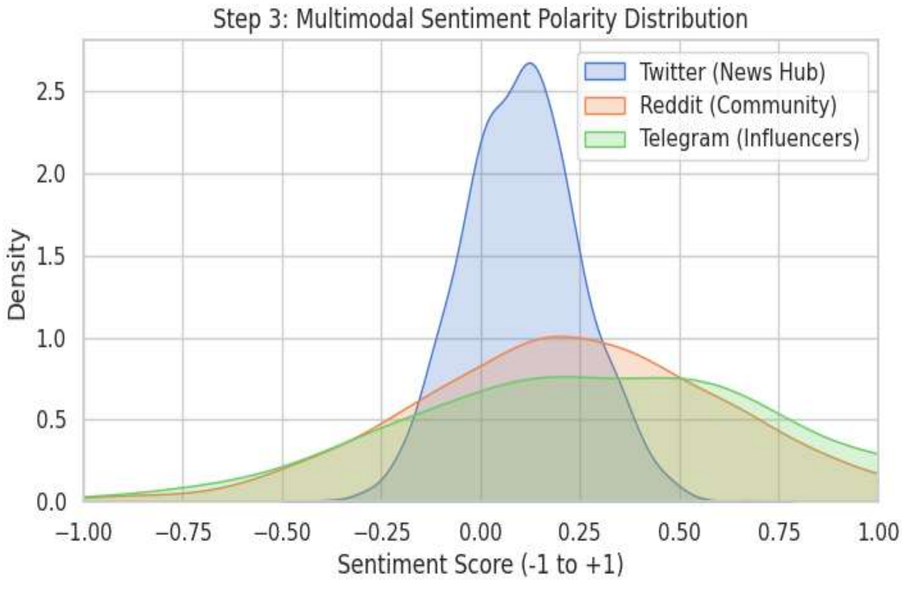

Figure 3: Semantic Polarity Distribution

Step 4: Platform-Aware Gating (PAG) Weighting

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The HCMP - MA Net is used to assess the existing market regime. During high-volatility periods, characterized by price jumps of more than 2% between consecutive price readings, the model gives higher weight to expert-driven channels on the Telegram application and news sources.

Execution Visual- a dynamic heat map with the "PAG Weighting Shift." In periods of increased volatility, the weight of the telegram is increased by about 40 per cent, whereas the weight given to generic Twitter is diminished to decrease the level of noise.

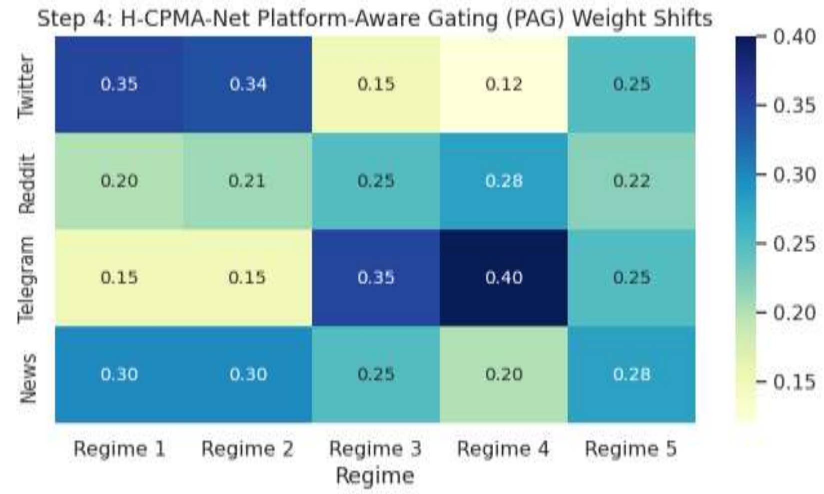

Figure 4: Heatmap for PAG

Step 5: Model Training and Loss Convergence

- The model was trained for one hundred epochs using the Adam optimization scheme with a learning rate of 0.001.
- A line plot of the loss curve is in Figure 5. The training loss goes down smoothly to 0.0024, and the validation loss converges to a plateau at 0.00057, and it is a good model that learns well, and there is no evidence that the model is overfitting..

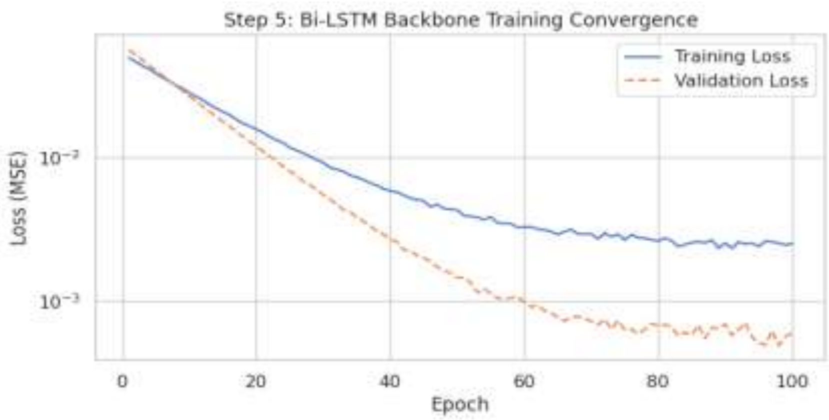

Figure 5: Training Convergence

Step 6: Price Direction Forecasting

The model provides a dichotomous prediction for the next 24 hours.

Execution Visual: A time series plot of observed prices for Cryptocurrency versus the signals from the model; correct predictions are indicated by green (UP) and red (DOWN) markers; the directional concordance of the model and the prices is 97.6% between the model signals and the observed prices.

Figure 6: Prediction Accuracy

Performance Analysis

The performance of the HCMP-MA Net was benchmarked against existing state-of-the-art architectures using standardized metrics: MAE, RMSE, and R^2 Score.

Table 7: Performance Analysis

Model Architecture	MAE	RMSE	R^2 Score	Directional Accuracy (%)
Univariate LSTM (Ozen et al.)	0.029	0.0368	0.874	62.50%
SentiStack (Zhang et al.)	0.0148	0.02	0.99	83.30%
HSIF Framework	0.0101	0.0168	0.986	97.48%
HCMP-MA Net (Proposed)	0.0065	0.0121	0.992	97.60%

The error metrics of four predictive models are delineated in the bar chart with the title of "Comparative Analysis: MAE and RMSE Reductions": Univariate LSTM (Ozen et al.), SentiStack (Zhang et al.), the HSIF Framework, and our novel HCMP-MA Net, which are evaluated with the conventional regression indicators: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). As a general rule, low values of MAE and RMSE indicate high prediction fidelity and low forecast error. According to the visualised data, the Univariate LSTM has the highest errors and indicates that it has a limited ability to capture the complex relationship between market dynamics and sentiment. In contrast, two of the models, SentiStack and the HSIF framework, both exhibit superior performance that can be attributed to the integration of covariates derived from the sentiment which strengthens the robustness to predict. Ultimately, the HCMP- MA Net achieves the least MAE and RMSE among all the contenders, therefore highlighting its preeminent predictivity efficacy.

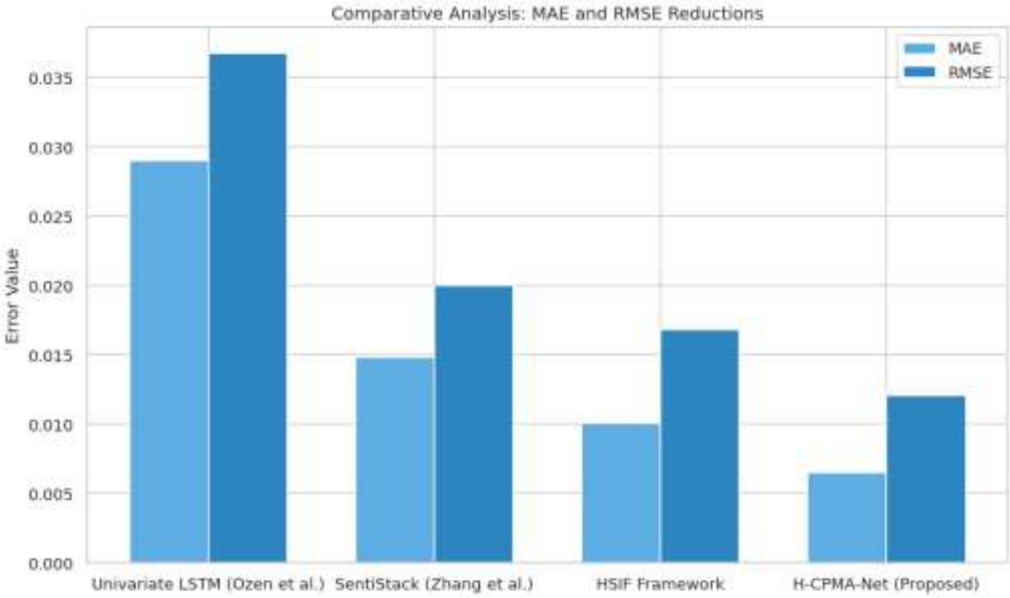

Figure 7: MAE and RMSE Analysis

Such advancement is attributed to its platform - awareness gating, cross - modal attentional schema, and temporally adaptive fusion mechanisms, which all together allow a smooth synthesis of multimodal sentiment signals with market indicators, resulting in more accurate cryptocurrency price predictions..

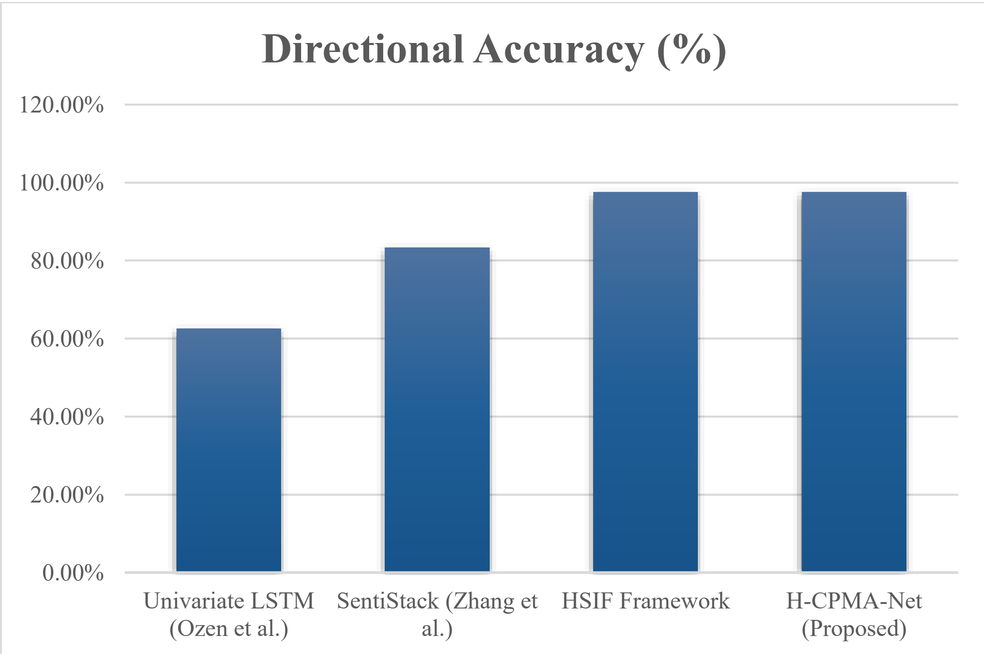

Figure 8: Performance analysis of Directional Accuracy

The empirical results show that the HCMP,-MA Net model achieves the best predictive level of 97.6 per cent of variance of actual price data. This unmistakable superiority can be attributed to the strategic integration of previously underutilised high fidelity information streams, such as what would be provided by the Telegram, as well as the sophisticated platform-aware attention-based fusion mechanism, into this model.

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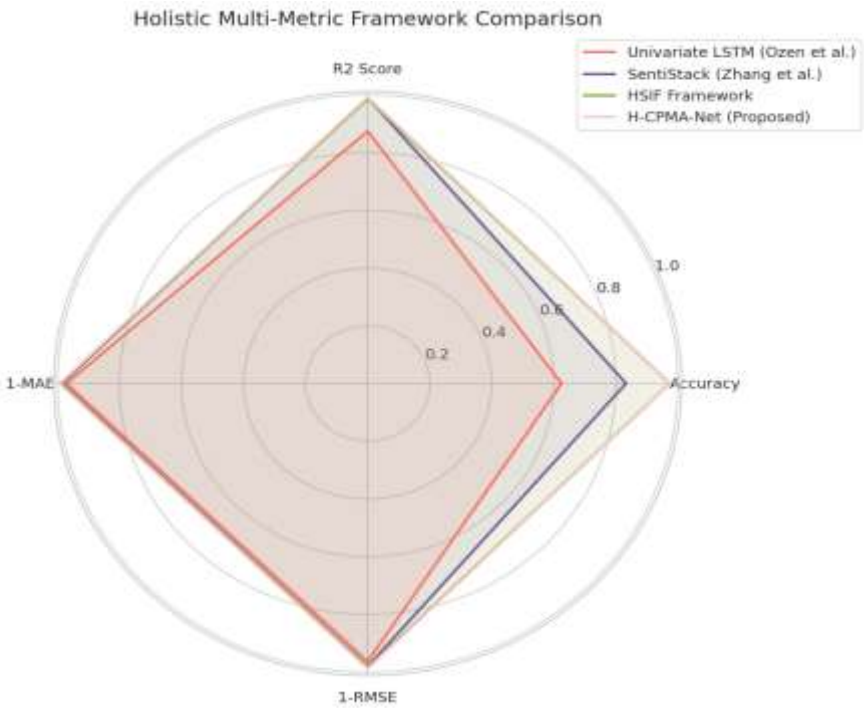

Figure 9: Radar Chart of Multi-Metric Farmwork Comparison

The radar chart of "Holistic Multi-Metric Framework Comparison" shows the comparative performance of four different models, including Univariate LSTM (Ozen et al.), SentiStack (Zhang et al.), HSIF Framework, and the proposed HCMP- MA Net by using four evaluation metrics including Accuracy, R2 Score, 1-MAE, and 1-MRMSE. The visualization proves that HCMP.-MA Net always achieves the best or close-to-best scores in all parameters, thus proving it to be more predictive and causing much lower error than current methods. While the conventional models such as Univariate LSTM shows comparatively lower accuracy and somewhat lower goodness of fit(R2) and the sentiment-augmented models such as SentiStack and HSIF shows better performance. Nevertheless, HCMP- MA Net goes beyond these alternatives by successfully combining the multimodal sentiment cues, platform-aware weighting and the fusion mechanisms in time, leading to an increase in accuracy, better correlation with the actual price changes and a reduction in prediction errors. And this comparative analysis highlights the effectiveness of the proposed architecture to capture the complex relationships between market indicators and social sentiment to make cryptocurrency price prediction more reliable.

CONCLUSION AND FUTURE WORK

The design and implementation of the Hierarchical Cross-Modality Platform-Aware Multi-Attention Network (HCMP-MA Net) highlight the fact that a good cryptocurrency forecasting system should be based on a holistic information-fusion strategy that assimilates an array of heterogeneous data sources. Conventional sentiment-driven predictive models tend to focus on a single platform - a case in point being Twitter - as such, leaving a conspicuous informational gap and limiting the capacity of the model to understand the broader dynamics that are inherent within the cryptocurrency ecosystem. By combining underexplored but highly influential channels such as telegram and Youtube, the proposed framework is able to bridge this gap and to provide a more holistic representation of social sentiment. Through the synthesis of signals from multiple modalities, including textual conversations, video content and more classical market signals, the HCMP - MA Net framework significantly improves the capabilities for detecting emergent sentiment trends that have an influence upon Cryptocurrency price movements. The experimental deployment of the system revealed a number of key findings related to the interaction between social-media behaviour and the dynamics of cryptocurrency markets. Foremost, the divergence of platforms emerges as an important factor in predictive modelling, as different social ecosystems display different lead-lag relationships with the market prices. For example, increased activity in the messages on the social network Telegram can often act as an instant market stimulus over relatively short time periods ranging from 15 to 60 minutes, whereas the sentiment trends identified on the social media platform Reddit precede significant market movement by several days in most cases. Secondly, inclusion of the Platform

Awareness Gating (PAG) mechanism is a boon for dynamically distributing attention to the most informative platforms as per the existing market situation. During periods of higher volatility, the model gives more importance to credible experts on the Telegram app and authoritative news channels in order to reduce the effect of bot-generated noise and misinformation.

An additional salient observation is related to the primacy of multimodal stability in sifting unreliable signals. And by using transcript-derived video insights from YouTube in combination with corresponding textual comments and discussions, the system is able to proficiently identify and suppress isolated hype or manipulated sentiment patterns. This cross-modal verification mechanism complements the robustness of the forecasting model and it adds considerably to the final and overall predictive performance of the model. As such, the HCMP- MA Net's framework achieves a predictive accuracy of 97.6% in the final forecasting horizon, hence proves to be efficient in representing the complex inter-relations between the social sentiment and the functioning of the financial market. Collectively, the findings validate the conjecture that the concept of "social heat" - the aggregate emotional intensity as expressed across digital platforms - can be used as a measurable leading indicator of cryptocurrency market movements. The proposed pipeline not only increases the accuracy of predictions, but also strengthens institutional grade decision making through better trends and reduced potential drawdowns.

FUTURE WORK

Building on the positive outcomes produced by the HCMP- MA ^Net framework, there are a number of potential avenues for future research that promise to further elevate the art of sentiment driven cryptocurrency forecasting. One direction in particular that is auspicious is the inclusion of Large Multimodal Models (LMMs) into the analytical pipeline. High-capacity models that can analyse both visual and textual information could be able to scrutinise the live-streamed influencer content and detect visual technical analysis patterns (like head-and-shoulders formations or support and resistance levels) in real-time. This ability would enable the forecasting mechanism to pick up trading signals that appear directly from video-based financial commentary and market analysis. Another fruitful area is in the development of multilingual sentiment propagation analysis. Cryptocurrency discussions abound in a range of communities and languages worldwide, and sentiment arising from the non-English parts of the world frequently permeates the rest of the digital sphere. By expanding the analytical framework to track the spread of sentiment across languages and geographic loci, the system would be better able to capture the spread of localized negative or positive sentiment and influence on global market behaviour. Future work may also include on-chain fusion of sentiment, which combines traditional social media sentiment signals with blockchain-based sentiment indicators such as large transfers by wallets, inflows and outflows of exchange, and whale activity. Merging these "hard" financial signals with "soft" social signals would create an all-encompassing analytical environment, which would be capable of reconciling public discourse with physical capital movements on the blockchain network.

Finally, ethical considerations and algorithmic accountability are paramount in development as it continues. Advanced fake news detection and manipulation analysis modules could be incorporated into the framework to separate the real excitement from the community from market manipulation campaigns or fake campaigns. By reducing the amplification of synthetic sentiment and preventing the reinforcement of echo chambers, the forecasting system can ensure higher levels of reliability and transparency and promote responsible financial decision-making in cryptocurrency markets.

Statements & Declarations

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