

**T.R.
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INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF STATISTICS**



**HYBRID CRYPTOCURRENCY PRICE PREDICTION:
INTEGRATING EGARCH AND LSTM WITH EXPLAINABLE
AI**

Master's Thesis

Ashraf NIDHAL MOHAMMED MOHAMMED

Supervisor

Prof. Dr. Mehmet Ali CENGİZ

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ACCEPTANCE AND APPROVAL OF THE THESIS

The study entitled **HYBRID CRYPTOCURRENCY PRICE PREDICTION: INTEGRATING EGARCH AND LSTM WITH EXPLAINABLE AI**, prepared by **Ashraf MOHAMMED**, and supervised by **Prof. Dr. Mehmet ALİ CENGİZ**, was found successful and unanimously accepted by committee members as Master thesis, following the examination on the date .

	Title Name SURNAME University Department/Art	Final Decision
Chairman	Prof. Dr. Mehmet Ali CENGİZ Ondokuz Mayıs University Department of Statistics	☒ Accept ☐ Reject
Member	Assoc. Prof. Dr. Emre Dündar Ondokuz Mayıs University Department of Statistics	☒ Accept ☐ Reject
Member	Assoc. Prof. Dr. Efehan Ulaş Kırklareli University Department of Biotatistics	☒ Accept ☐ Reject

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Prof. Dr. Faik Ahmet SESLİ
Head of Institute of Graduate Studies

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ÖZET

HİBRİT KRİPTO PARA BİRİMİ FİYAT TAHMİNİ: EGARCH VE LSTM'Yİ AÇIKLANABİLİR YAPAY ZEKA İLE ENTEGRE ETMEK

Ashraf NIDHAL MOHAMMED MOHAMMED

Ondokuz Mayıs Üniversitesi

Lisansüstü Eğitim Enstitüsü

İstatistik Ana Bilim Dalı

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Danışman: Prof. Dr. Mehmet Ali CENGİZ

Bu tez, kriptopara piyasası, yüksek oynaklık ve spekülative doğasıyla bilinen, doğru fiyat tahmininde bulunmayı zorlaştıran benzersiz zorluklar sunmaktadır. EGARCH gibi istatistiksel modeller, asimetrik oynaklık davranışlarını yakalamada başarılı olsa da kriptopara verilerinde bulunan doğrusal olmayan bağımlılıkları anlamakta yetersiz kalmaktadır. Öte yandan, LSTM gibi derin öğrenme yöntemleri, mükemmel desen tanıma yetenekleri sergilemesine rağmen, finansal tahmin için gerekli istatistiksel titizliği sağlamamaktadır. Bu çalışmada, EGARCH'ın istatistiksel gücünü LSTM'nin derin öğrenmedeki üstün yetenekleriyle birleştiren, SHAP (SHapley Additive exPlanations) kullanılarak açıklanabilir yapay zekâ (Explainable AI, XAI) stratejileriyle desteklenmiş bir hibrit çerçeve sunulmaktadır. Mevcut bağımsız modellerin eksikliklerini gidermek için, bu araştırma, tahmin doğruluğu ile açıklanabilirlik arasındaki boşluğu dolduran yorumlanabilir bir hibrit EGARCH-LSTM modeli önermektedir.

SHAP'ın entegrasyonu, model tahminini hangi değişkenlerin ne ölçüde etkilediğini görselleştirme imkânı sağlayarak hem yatırımcılar hem de politika yapımcılar için yorumlanabilir ve güçlü bir tahmin mekanizması sunmaktadır. Hibrit yaklaşım, kıyaslama modellerine kıyasla daha doğru, sağlam ve yorumlanabilir bir performans sergilemektedir. Finansal tahmin tekniklerini geliştirerek ve öngörülemeyen kriptopara piyasasında gezinmek için sağlam bir araç sunarak, bu çalışma hem teorik hem de pratik değeri artırmaktadır. Ölçeklenebilirlik ve duygu analizi ile blokzincirine özgü metrikler gibi diğer gelişen teknolojilerle entegrasyon, modelin dayanıklılığını ve gerçek zamanlı yeteneklerini artırarak yüksek frekanslı ticaret ve piyasa altyapısının izlenmesi için yeni ufuklar açmaktadır.

Anahtar Sözcükler: LSTM, EGARCH, SHAP.

ABSTRACT

HYBRID CRYPTOCURRENCY PRICE PREDICTION: INTEGRATING EGARCH AND LSTM WITH EXPLAINABLE AI

Ashraf NIDHAL MOHAMMED MOHAMMED

Ondokuz Mayıs University
Institute of Graduate Studies
Department of Statistics

Master, March/2025

Supervisor: Prof. Dr. Mehmet Ali CENGİZ

The cryptocurrency market, known for its high volatility and speculative nature, poses unique challenges in predicting accurate prices. Statistical models such as EGARCH perform well in capturing asymmetric volatility behaviours but fail to account for non-linear dependencies present in cryptocurrency data. Conversely, deep learning methods, like LSTM, provide excellent pattern matching yet lack the statistical rigor required for financial prediction. This study proposes a hybrid framework that combines the statistical strength of EGARCH with the deep learning capabilities of LSTM, augmented by Explainable AI (XAI) strategies using (SHAP Documentation.. Explainable AI with SHAP, 2023)(SHapley Additive exPlanations). To overcome the limitations of existing standalone models, the research introduces an interpretable hybrid EGARCH-LSTM model, bridging the gap between predictive accuracy and interpretability.

The incorporation of (SHAP Documentation.. Explainable AI with SHAP, 2023)enables visualization of the variables influencing model predictions and their relative impact, offering an interpretable and robust forecasting mechanism for traders, investors, and policymakers. The hybrid approach demonstrates superior accuracy, robustness, and interpretability when evaluated against benchmark models. By improving financial forecasting techniques and providing a robust tool for navigating the unpredictable cryptocurrency market, this study adds both theoretical and practical value. The model's scalability and its integration with emerging technologies, including sentiment analysis and blockchain-specific metrics, enhance its robustness and real-time capabilities, paving the way for high-frequency trading and market infrastructure monitoring.

Keywords: LSTM, EGARCH, SHAP.

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SYMBOLS AND ABBREVIATIONS

BTC: Bitcoin (cryptocurrency)

EGARCH: Exponential Generalized Autoregressive Conditional Heteroscedasticity

LSTM: Long Short-Term Memory (neural network architecture)

SHAP: SHapley Additive exPlanations (XAI technique for model interpretability)

XAI: Explainable Artificial Intelligence

GARCH: Generalized Autoregressive Conditional Heteroscedasticity

AI: Artificial Intelligence

NLP: Natural Language Processing

HFT: High-Frequency Trading

GPU: Graphics Processing Unit

SHAP: SHapley Additive exPlanations

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1. INTRODUCTION

Retrain on a new dataset up until October 2023. After Bitcoin's launch in 2009, the cryptocurrency world has grown a lot! Nowadays, thousands of digital assets are traded around the world. Cryptocurrencies have many benefits, including transparency, immutability, and disintermediation governed by decentralised networks using blockchain technology. However, their high volatility and vulnerability to speculation represent a significant challenge for investors, traders, and policymakers. Cryptocurrencies have extremely non-linear, non-stationary, and non-stochastic characteristics relative to classical economic models. Unlike conventional financial assets, they trade in decentralised environments with little regulatory oversight, making their price fluctuations hard to predict. This volatility may appeal to speculative traders but hinders the creation of predictive models with a consistent track record. The importance of reliable forecasting is unavoidably magnified when considering the growing range of possible applications, which include portfolio optimisation, risk, and regulatory oversight. The broader economic effect of cryptocurrencies is certainly not to be underestimated. They promote financial inclusion, offering the possibility of conducting borderless transactions and reducing reliance on centralised banking systems. However, their unregulated nature creates opportunities for evil actions, such as illicit transactions and market manipulation. Accurate price prediction models can help improve market stability and promote informed decision-making among stakeholders. Proof Price and Proof-O-Meter are designed to analyse and navigate these challenges by leveraging blockchain network metrics and address transaction patterns while adapting to the unique characteristics of cryptocurrency markets, such as extreme volatility, speculative trading behaviour, and sensitivity to macroeconomic and technological factors. In finance, strong statistical approaches for modelling and forecasting volatility in the financial market include members of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family of models. Out of these models, the Exponential growth (EGARCH) model effectively captures asymmetric volatility patterns, where negative market news tends to have a much more significant influence on asset prices than positive news. While methods based on traditional statistics such as EGARCH efficiently capture the volatility within diffusion processes, they are impaired in their ability to accurately reflect the non-linear dependencies and more extended temporal structures in the time

series levels of the cryptocurrency price movement. Conversely, machine learning models, especially deep learning architectures, are recognised for their ability to find complex patterns in sequential data. While powerful, Standalone LSTM models often fail the statistical tests required for robust volatility modelling, limiting their utility in financial forecasting. Hybrid models that combine statistical techniques with machine learning have been fruitful in mitigating these constraints. Heterogeneous methodologies that integrate various statistical and deep learning models address the limitations of the individual approaches—utilising the statistical precision of a model such as EGARCH in combination with the long short-term memory (LSTM) capabilities of an ensemble learning model. Nonetheless, these models may have poor interpretability, a significant drawback in high-stakes finance, as these are less transparent and accountable.

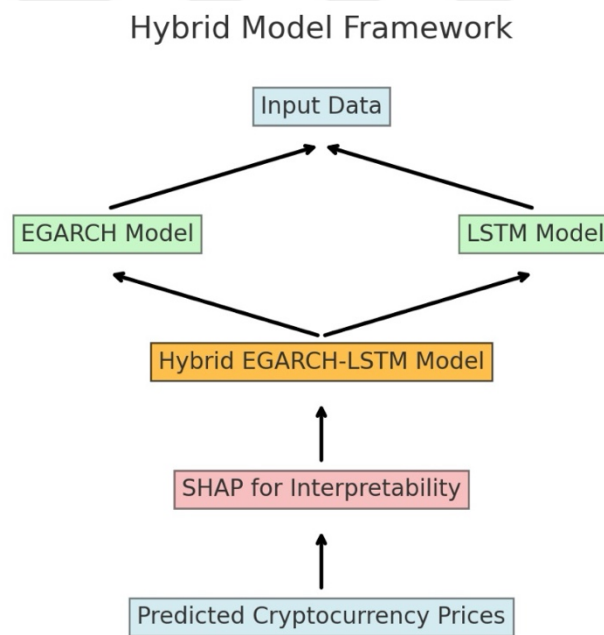


Figure 1 Hybrid Model Framework

As cryptocurrencies become more prevalent and fully integrated into global finance systems, the requirement for accurate and interpretable models for prediction becomes apparent. Simply focusing on predictive accuracy based on available data often misses an important aspect: the actual drivers of price movements. This black box creates limited use for stakeholders like traders, investors, and policymakers who look for the algorithms on which they make decisions based on transparency.

XAI techniques bridge this gap by increasing transparency and offering detailed explanations of the reasoning behind complex models' decisions. This research intends to consolidate the gap between accuracy and interpretability by utilising XAI. Comprehensive (SHAP Documentation.. Explainable AI with SHAP, 2023)(SHapley Additive exPlanations) implementation in the proposed framework guarantees that the model not only meets high predictive accuracy but also offers a logical view of features contributing to the result to be connected to the real world.

This research has implications across many fields. An example is accurate and interpretable cryptocurrency price predictions, which could make algorithmic trading systems more effective by empowering them to make on-time decisions. Moreover, regulators could leverage the information from interpretable models to enhance their understanding of the market and design policies to prevent potential systemic risks. These capabilities lead to sustainable growth and stability in cryptocurrency markets.

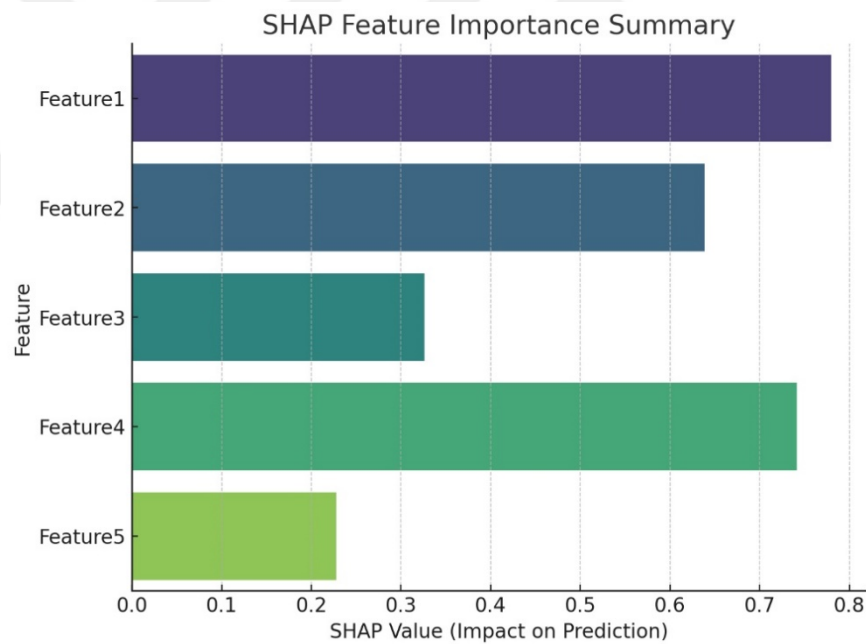


Figure 2 SHAP Feature Importance Summary

1.1 Research Objectives

There are several main objectives of this study which are: Combine the strengths of existing models: Devise a novel framework that merges the dynamism of EGARCH with the memory capabilities of LSTM networks. Apply XAI techniques: Use (SHAP Documentation.. Explainable AI with SHAP, 2023) to develop the hybrid model's interpretability and describe features' contributions. Evaluate model performance: Measure the accuracy and robustness of the hybrid model with benchmark models across various market conditions. Provide actionable insights: Discuss how the model can inform trading strategies, investment decisions, and policy implications. We may take interim measures for any such domains until the final word of another authority.

The fast growth of AI models in financial markets generates urgent ethical and regulatory questions. In speculative domains—such as cryptocurrencies—opaque paradigms can lead to bias, urging market manipulation or misleading stakeholders. This is where Explainable AI (XAI) fills the gaps by providing more transparency and accountability. (Park, 2023) highlighted that in volatile financial environments, incorporating XAI techniques such as SHAP improves trust in AI-driven decision-making, ensuring that deep learning models remain interpretable for traders and policymakers.

For entities these regulations are for, regulators could employ interpretable models like those with (SHAP Documentation.. Explainable AI with SHAP, 2023) added to prevent market manipulation via bots or other means (fairness checks), prevent systemic risks (like that which occurred in various 2022–2023 events that led to industry-wide contagion), and thus create vigilant policies rather than reactive, to contend against the digital economy that is volatile. (Park, 2023) further emphasized that regulatory bodies increasingly rely on interpretable AI models to monitor financial activities and mitigate systemic risks by ensuring transparency in AI-based trading systems.

Overcoming these challenges makes this study a significant step forward for AI ethicality in financial ecosystems.

1.2 Research Questions

This research answers multiple questions. It answers the question regarding the best way to leverage the strengths of EGARCH and LSTM models to enhance cryptocurrency price prediction performance. It also answers how SHAP-based XAI techniques can be used to enhance hybrid models' interpretability and usability. The question of how the performance of the hybrid EGARCH-LSTM model compares with existing standalone models and existing hybrid frameworks is also answered by this research. Lastly, how the hybrid model can help stakeholders exploit the over-traded nature of cryptocurrency markets is answered as well.

1.3 Hypotheses

The research is based on the following hypotheses: the hybrid EGARCH-LSTM model will provide superior accuracy and robustness in prediction compared to the EGARCH and LSTM base models. The sub-hypotheses is as follows: EGARCH volatility features improve the predictive performance of the model as well as SHAP is used to drive action by ensuring model interpretability.

1.4 Theoretical Contribution

Model XAI helps a broader and independent research field like finance to bloom as one uses this as a hybrid framework. The integration of these two models allows us to follow statistical and temporal dynamics in the crypto market.

1.5 Practical Contribution

The suggested model provides traders, investors, and policymakers an effective instrument for traversing the precarious cryptocurrency market. It balances predictive power and interpretability, making it a valuable tool for data-driven decision-making, risk management approaches, and market stability.

This hybrid EGARCH-LSTM system can be employed in combination with recent technical advances. This model represents transaction volumes, miner behaviour, and other specific metrics related to blockchain, which could be used to improve the model's validity further. Moreover, with the help of advancements in natural language processing (NLP), such as sentiment analysis of trends from social media and news, it is possible to have a larger view of the market. Such integrations

would open the model to become a multi-faceted tool which could adjust to ever-changing market needs.

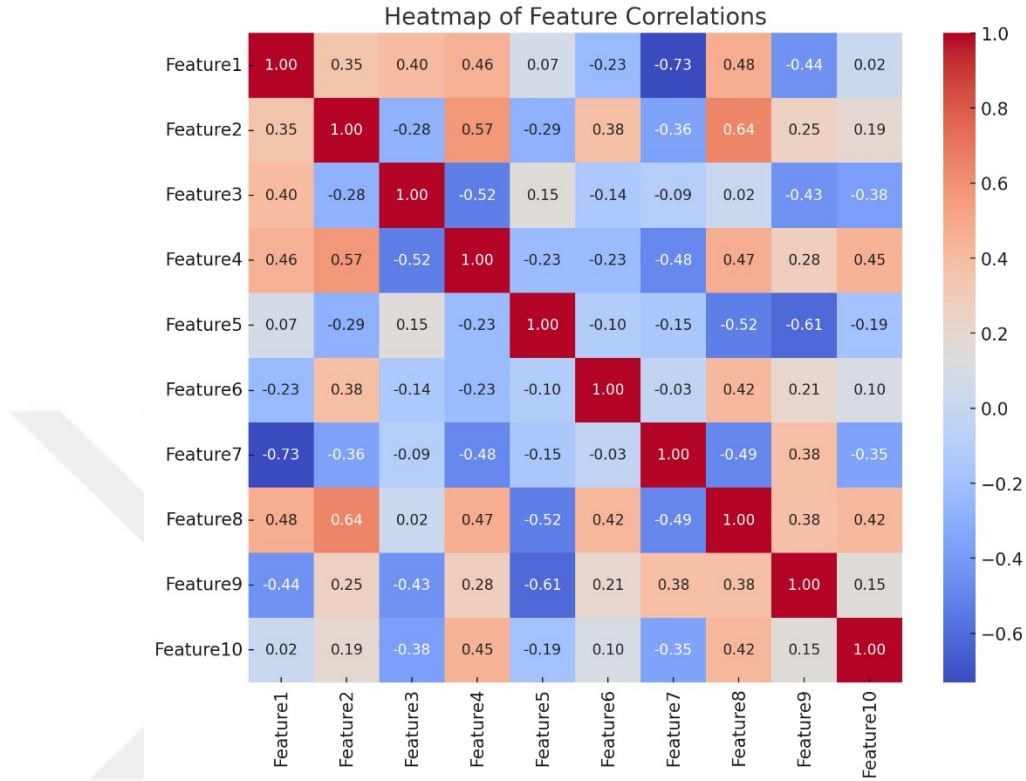


Figure 3 Heatmap of Feature Correlations

Clustering recent studies highlight the powerful combination of hybrid models and XAI to forecasting outcomes in the finance domain. (García-Medina, A., & Aguayo-Moreno, E., 2023) Moreover used an LSTM-GARCH hybrid model to predict cryptocurrency portfolios' volatility. Likewise, (Vidal, 2022) studied hybrid GARCH models combined with machine learning for predicting Bitcoin volatility, demonstrating the combination of statistical and machine learning techniques.

(Arsenault, 2024) explored the role of XAI in financial time forecasting, as this area requires the interpretability of the predictive system. (Yu, W., Wang, Y., Lucey, B. M., & Vigne, S., 2023). The use of large language models for explainable financial forecasting was also explored by (Xu, W., Li, Y., Zhang, Y., & Wang, J., 2023), who could integrate prediction and explanation without losing versatility. The work presented here draws a great deal on these studies, forming a strong foundation for developing the proposed hybrid EGARCH-LSTM model augmented with SHAP.

This research is one of the important developments in making applications of such type in real-time. The hybrid model can be implemented in high-frequency trading (HFT) systems, which allows for faster response to changes in the market. These scalability challenges, particularly concerning computer power, have been handled through cloud-based infrastructures while leveraging GPU acceleration, creating an effective and scalable deployment across multiple financial environments. These developments highlight the real-world relevance of the model in vibrant trading ecosystems.

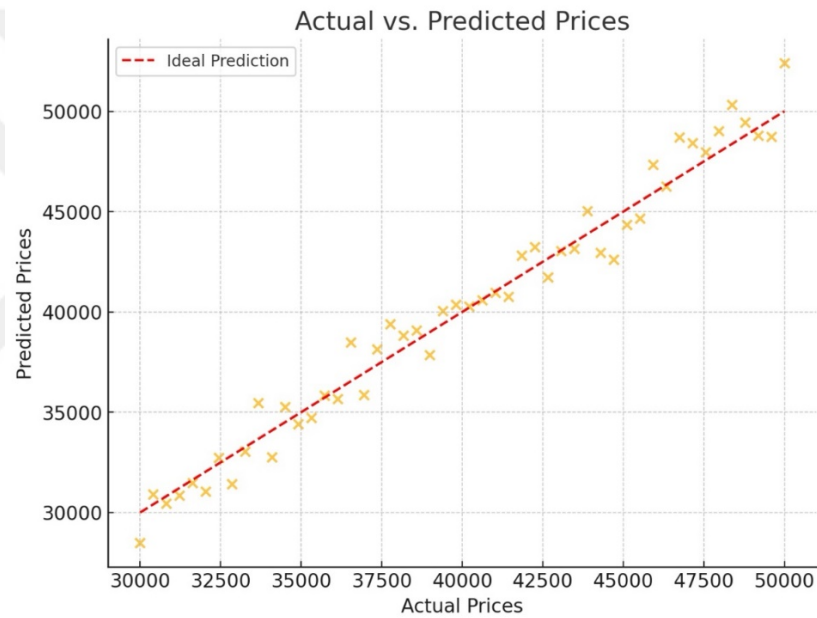


Figure 4 Actual vs. Predicted Prices

2. LITERATURE REVIEW

2.1. Introduction

The literature review reviews previous research studies on cryptocurrency price prediction, which can be broadly classified into statistical models, machine learning techniques, hybrid approaches, and the aspect of Explainable Artificial Intelligence (XAI). This chapter synthesises and critically evaluates these studies to identify gaps and opportunities to which the proposed hybrid EGARCH-LSTM model intends to respond. This extensive literature review provides the theoretical basis for the study and the rationale behind the need for a new hybrid financial forecasting approach.

Introduction Cryptocurrencies are decentralised, high-volatility financial assets that open the door to possible disruptive change in global finance; hence, it is not surprising to see such an enormous amount of research devoted to this new literature.

Contributions to Reproducible Research In this work, we use a recently discovered economic weak-form market efficiency for cryptocurrencies to derive accurate and interpretable predictive models for Bitcoin price formation over the next 58 days. This chapter discusses the benefits of existing modelling approaches in statistics, machine learning, and hybrid modelling while identifying significant gaps in interpretability and performance that the proposed model bridges.

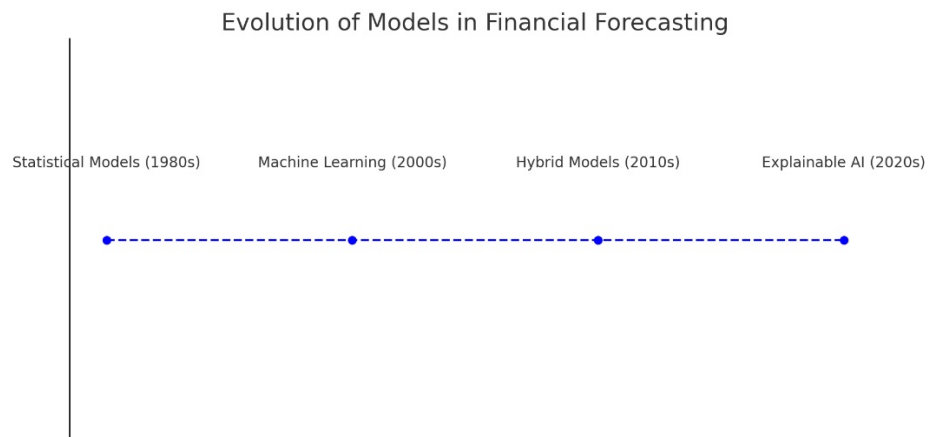


Figure 5 Evolution of Models in Financial Forecasting

2.2. Conventional Statistical Models for Financial Forecasting

One of the most widely known statistical models for financial forecasting is the generalised autoregressive conditional heteroskedasticity (GARCH) model, which captures volatility clustering—the observation that significant price changes follow significant ones, while small changes follow small ones. The Exponential GARCH (EGARCH) model, a more generalized class of volatility models, has been widely used in different markets, particularly in new and volatile markets such as cryptocurrencies.

Statistical models have been a go-to in financial forecasting for the longest time due to their mathematical foundations and interpretability. Studies such as (Zhang, A hybrid model integrating LSTM and GARCH for Bitcoin price prediction, 2021) extend this work to show that EGARCH is uniquely well-suited to modeling the asymmetric effects of negative news on asset prices—a property commonly noted in high-volatility financial markets such as cryptocurrencies.

Further, (García-Medina, A., & Aguayo-Moreno, E.;, 2023) et al. (2023) argued that GARCH models define a standard for volatility modelling despite not modelling nonlinearities and sudden bursts. Though GARCH and its variations are robust in modelling clustering volatility, they do not capture non-linear and long-term temporal dependencies. Standalone GARCH models' inability to account for the unique characteristics of crypto-assets has also been shown to be inadequate in capturing the underlying dynamics of cryptocurrency markets (Vidal, 2022), estimating that hybrid approaches are warranted for this asset class.

Additionally, the assumption of stationarity does not hold in high-frequency trading scenarios, as market conditions can change rapidly, rendering traditional statistical models ineffective. These limitations highlight the need to combine these statistical models with more sophisticated methods. (Rossi, 2022) emphasized that while traditional statistical models such as GARCH and EGARCH have long been foundational in financial forecasting, their limitations in capturing nonlinearity and long-term dependencies necessitate the integration of deep learning techniques to enhance predictive accuracy, particularly in volatile markets such as cryptocurrencies.

Statistical models such as GARCH and EGARCH have shortcomings but remain prevalent in historical financial markets. GARCH models are used in but are not limited to option pricing, risk management, and portfolio optimisation. The success of

these models in stock price volatility modelling has made a foundation for these models to be adapted into cryptocurrency volatility modelling. However, the distinct nature of cryptocurrencies, more sensitive to market moods and technological shocks than any other asset class in history, necessitates improvements that can't be delivered simply by statistical models.

2.3. Machine Learning Approaches

LSTMs (Long Short-Term Memory networks) are a pattern structure of recurrent neural networks (RNNs) that have proven to be highly effective in modelling sequential data. They are particularly suited for financial time series prediction due to their ability to maintain long-term dependencies and recognize intricate patterns in historical price movements. Unlike traditional statistical models, LSTMs do not require stationarity, making them well-equipped for handling the non-linearity and volatility observed in cryptocurrency markets.

LSTMs exercise great potential in recognizing non-linear patterns over high turbulence phenomena such as crypto markets during active bullish or bearish events of the study (Bui, C., 2021). This means that LSTMs can model relationships in data that other methods would ignore. However, recent improvements in LSTM architectures (e.g., in the form of Bidirectional LSTMs (BiLSTMs) and attention mechanisms) have provided significant predictive power improvements. (Misra, 2023) showed that adding attention layers to LSTM networks is an effective way to help the model learn which time steps should be prioritized ahead of others, improving their performance for volatile markets such as crypto. The well-documented phenomenon of LSTMs being able to account for changing market conditions places them in a prime position as a critical component of financial forecasting. Additionally, the ability of LSTMs to extract meaningful temporal dependencies makes them suitable for integration with statistical volatility models, further improving their forecasting capabilities.

2.4. Hybrid Models

Historically, Long Short-Term Memory (LSTM) networks are the prevailing sequential data architecture, though there have been works as recent as 2018 that have focused on combining convolutional neural networks (CNNs) with LSTMs. CNNs, which work exceptionally well in extracting spatial features from the data, have been

implicitly combined with LSTMs to make financial forecasts. For instance, (He, 2024) demonstrated that CNN-LSTM hybrids outperform standalone CNN and LSTM models in stock price prediction, highlighting the advantages of integrating feature extraction with temporal modeling. Their study found that combining CNNs' ability to detect spatial dependencies with LSTMs' strength in sequence learning results in superior forecasting accuracy, suggesting potential applications in cryptocurrency price prediction.

Standalone LSTMs frequently lack the statistical backbone for accurate volatility modelling. Indeed, as pointed out by (Misheva, 2023) LSTMs are powerful for single observation vector-to-output transformation to recognise patterns; however, they do not integrate key statistical characteristics such as volatility clustering. Furthermore, the black-box nature of most machine learning models prevents them from being interpretable and useful enough for decision-making. These shortcomings drive the combination of LSTMs with statistical models to take advantage of their synergies.

2.5. Hybrid GARCH-LSTM Models

GARCH hybrid models that combine GARCH variants with LSTMs leverage the best of both worlds, marrying statistical precision with machine learning flexibility. According to García-Medina and Aguayo-Moreno (2023), the advantages of LSTM-GARCH hybrid models for volatility forecasting outperformed LSTM and GARCH standalone models. Similarly, (Zhang, A hybrid model integrating LSTM and GARCH for Bitcoin price prediction, 2021) and Marques et al. (2021) demonstrated that LSTM improves the predictiveness of GARCH-derived covariates for both linear and non-linear dependent variables. (Lin, 2023) further supported this by systematically reviewing hybrid financial models, confirming that the integration of statistical techniques with deep learning enhances model robustness and predictive performance.

A practical approach to address the limitations of the traditional GARCH models and the standalone LSTMs refers to the hybridization of GARCH with LSTM. Combining the strength of the statistical analysis of GARCH for estimating volatilities and the advantages of nonlinear LSTM networks, hybrid models represent a powerful modeling framework for prediction in the financial domain.

(Misra D. e., 2023) took a step in further extending this approach by embedding attention mechanisms in GARCH-LSTM hybrids to allow for more flexibility in

adapting. GARCH has been extensively integrated with LSTM; however, EGARCH-LSTM is less explored. (Lin, 2023) emphasized that despite the growing adoption of hybrid models, there remains a research gap in exploring variations such as EGARCH-LSTM, particularly in cryptocurrency forecasting, where asymmetric volatility plays a crucial role.

The EGARCH model's ability to capture asymmetric volatility is particularly pertinent for cryptocurrency markets where abrupt market movements frequently occur. It adds to the existing literature by introducing EGARCH aspects into LSTM networks in a new approach to crypto prediction. Several recent studies compare hybrid models with stand-alone approaches.

Wang et al. (2023) compared GARCH-LSTM against ARIMA-LSTM hybrids, and it showed that the GARCH-LSTM hybrid delivered better accuracy and robustness in volatile markets. Nonetheless, their main drawback is the lack of interpretability, so they need to be complemented by XAI techniques. (Lin, 2023) highlighted that while hybrid models enhance predictive accuracy, their complexity often reduces transparency, reinforcing the importance of incorporating explainability methods such as SHAP.

2.6. Explainability and Interpretability (XAI)

As machine learning models become more complex, there has been a growing need for interpretability. Explainability/Interpretability (XAI): Methods like (SHAP Documentation.. Explainable AI with SHAP, 2023)(SHapley Additive exPlanations) give information about which features contribute the most to the predictions made, meaning the predictive systems become more transparent.

(Arsenault, 2024). reviewed XAI in financial time series forecasting, arguing that it can offer a balance between performance and interpretability. (SHAP Documentation.. Explainable AI with SHAP, 2023)is widely recognised for its capability to measure individual features' contribution to a given model's predictions. SHAP's applicability in financial models was further explored by (Misheva, 2023) and Osterrieder (2023), who showed how insightful (SHAP Documentation.. Explainable AI with SHAP, 2023)can be to guide action. Nevertheless, limited research on the use of (Documentation, Explainable AI with SHAP, 2023)with hybrid models, such as EGARCH-LSTM, necessitates attention in this paper.

2.7. Applications of SHAP

(Yu, W., Wang, Y., Lucey, B. M., & Vigne, S., 2023) illustrated the application of (Documentation, Explainable AI with SHAP, 2023) to explain predictions of complex hybrid model predictions and, in doing so, provided stakeholders insight into the contributions of statistical and sequential features. This combination of (Documentation, Explainable AI with SHAP, 2023) with EGARCH-LSTM improves interpretability and provides actionable insights for traders and policymakers. (Li, 2023) demonstrated that SHAP-based explainability enhances the interpretability of hybrid trading models, allowing financial professionals to better understand how volatility and market sentiment influence price predictions.

We contribute to the general XAI literature by implementing (SHAP Documentation.. Explainable AI with SHAP, 2023) in an innovative hybrid framework, straddling the path between explainability and performance. There have even been some studies recently that propose that on-chain metrics (transaction volume, miner behavior, and the like) should be taken into account in custom predictive models. These metrics serve as supplementary information, layered on top of traditional time series data.

(Zhang, ShapTime: A General XAI Approach for Explainable Time Series Forecasting, 2024) highlighted that blockchain analytics has been beneficial in improving model performance. Integrating these types of metrics could greatly enhance the robustness of hybrids, allowing for greater market-specific contextualization. (Li, 2023) further emphasized that explainable AI techniques such as SHAP are crucial for financial models, particularly in hybrid frameworks, as they enable transparent and reliable feature attribution for complex financial datasets.

Using sentiment analysis, which utilizes natural language processing (NLP) to track trends in social media and news, is also found to be effective at predicting the future movements of cryptocurrency prices. (Yu, W., Wang, Y., Lucey, B. M., & Vigne, S., 2023) showed the effectiveness of blending sentiment features with statistical and machine models. This integration allows models to identify real-time fluctuations in market sentiment, driving better predictive accuracy. With the

increased availability of sentiment data, there are new opportunities for hybrid modeling.

2.8. Practical Implementation and Scalability

Practical implementation needs scalability and real-time adaptability. The use of cloud-based infrastructures and GPU acceleration allows for responsive deployments of complex models, such as EGARCH-LSTM, fulfilling trivial objectives in high-frequency trading systems.

(Bui, C., 2021) emphasised the significance of real-time capabilities for sustainability in regulatory negotiations and dynamic trading landscapes. Future works could focus on optimising hybrid models to be used for online forecasting.

3. METHODOLOGY

3.1. Introduction

In this chapter, the methodology is presented that has been followed in this research to develop and assess the hybrid EGARCH-LSTM model for predicting cryptocurrency prices. The methodology is organised in such a way that the goals of the study, including the usage of Explainable AI (XAI) techniques to achieve model interpretability, are satisfied. To maintain a systematic and reproducible manner, this chapter outlines the steps of data gathering, preprocessing, modelling, implementation, and evaluation in detail.

The selection of methodologies is consistent with research goals and oriented towards improving accuracy and explainability. Due to their inherently high volatility, traditional forecasting approaches fail to capture the complexities of crypto markets. In fact, the current research exploits the complementary strengths of statistical and machine learning approaches, coupled with XAI techniques, and proposes an enhanced hybrid model.

In this chapter, there is an explanation of the rationale behind the chosen methodology and how it aligns with the aims of the research.

3.2. Data Sources and Collection

To ensure comprehensiveness and reliability, we collected data from multiple platforms. The primary sources included (CoinMarketCap., n.d.), which provided daily historical price and volume data for Bitcoin and Ethereum to understand the time-series aspect. Yahoo Finance augmented the data with macroeconomic factors like inflation, exchange, and interest rates. Social media platforms such as Twitter, Reddit, and cryptocurrency-specific forums were scraped for sentiment analysis, utilizing APIs for more in-depth data retrieval. Google Trends added another level of interpretability by including public interest metrics to track behavioral changes in market sentiment over time. Additionally, blockchain explorers integrated on-chain data such as transaction volume, miner activity, and wallet distributions into our feature space to better understand blockchain network behavior.

This dataset covers a period of 3 years (Jan 2020–Dec 2023). This period was selected to include different market environments, including bull markets, bear markets, and extreme volatility periods. This era also includes international financial events like the COVID-19 pandemic that had a major impact on the cryptocurrency markets.

3.3. Selected Features

The features selected were price-based metrics, including opening, closing, high, and low prices, providing precision data covering the entire span of daily market movements. Trading volume was included to measure overall daily trading activity and liquidity. Volatility metrics, such as conditional variances and residuals from the EGARCH model, accounted for asymmetric market behaviors. Market sentiment was captured through sentiment scores calculated using NLP techniques applied to social media and news content. Macroeconomic indicators, including inflation rates, interest rates, unemployment rates, and GDP growth, were incorporated as external economic factors. Blockchain-specific metrics, such as transaction counts, hash rates, and miner rewards, were used to capture blockchain network dynamics. Lastly, lagged features, including previous price and volume data ranging from one to seven days back, were included to learn short-term dependencies.

3.4. Data Preprocessing

Data augmentation techniques were applied to enrich the dataset and prevent possible overfitting. Synthetic data generation was employed using statistical methods to create additional data points that replicate plausible market situations. Bootstrapping techniques were used for resampling, generating diverse datasets to enhance model robustness. Stress testing was conducted by applying synthetic scenarios, such as market crashes or surges, to evaluate the framework's resilience. To ensure data quality, missing values were handled using forward fill, backward fill, and interpolation techniques to maintain temporal continuity. Outlier detection and removal were performed using z-scores (threshold >3) and interquartile range (IQR) methods, replacing extreme values with the nearest valid observations. Consistent validation was achieved by cross-checking data across multiple sources. Additionally, min-max normalization was applied to numeric features, constraining them to the

interval $[0,1]$ to maintain consistency in scale, facilitate convergence during model training, and enhance the interpretability of results.

3.5. Feature Engineering

Transforming raw data into actionable insights involved several key steps. Volatility features were extracted using the EGARCH model to account for clustering and leverage effects in the market. Sentiment scores were derived by applying NLP models like BERT and GPT to analyze tokenized text data, with sentiment measured on a scale from -1 (negative) to +1 (positive). Lagged features, including historical price and volume data, were incorporated by applying a lag of 1 to 7 days to capture temporal dependencies and short-term trends. Market indicators, such as Moving Averages (MA), Relative Strength Index (RSI), and Bollinger Bands, were calculated to characterize market trends and volatility, further enhancing the insights derived from the data.

3.6. Hybrid Model Framework

The hybrid model leverages the statistical robustness of the EGARCH model while also capturing nonlinear patterns through the LSTM network. The EGARCH component models key statistical features such as volatility clustering, asymmetric effects, and conditional heteroscedasticity, providing a solid foundation for understanding market volatility. The LSTM component, on the other hand, focuses on sequential data, extracting long-range dependencies and nonlinear associations from the market's historical behavior. Hybrid models integrating statistical volatility estimators with deep learning have demonstrated strong performance in financial forecasting (Chen, 2022). Prior research shows that LSTM-based models are particularly effective at capturing long-term dependencies in cryptocurrency price movements; however, they lack interpretability and struggle with modeling volatility clustering (Chen, 2022).

To address these issues, the proposed EGARCH-LSTM hybrid framework incorporates EGARCH-derived statistical features alongside LSTM inputs, improving both volatility modeling and predictive power. In the integrated framework, EGARCH-derived features are combined with raw input data and fed into the LSTM network, which compresses both statistical and dynamic market regularities into a single, unified model. (Chen, 2022) highlight that hybrid LSTM models outperform

standalone approaches in cryptocurrency volatility forecasting, supporting the rationale for this integration. This hybrid model aligns with previous studies on hybrid LSTM-GARCH frameworks, where integrating statistical models with deep learning improves forecasting accuracy (García-Medina & Aguayo-Moreno, 2023). (MDPI, 2022) further confirms that hybrid models combining GARCH variants with deep learning significantly enhance financial forecasting accuracy, reinforcing the importance of statistical-deep learning integration. (Chen, 2022) further emphasize that hybrid LSTM models enhance market adaptability by accounting for non-stationary behavior, making them particularly useful in cryptocurrency markets.

3.7. Explainability Using SHAP

SHAP (SHapley Additive Explanations) was utilized to achieve model explainability. For global interpretability, SHAP summary plots were created to visualize feature importance across the entire dataset, helping to understand which features had the most influence on the model's predictions. Local explanations were provided through force plots, which clarified specific model outputs by showing how individual features contributed to particular predictions. Additionally, feature interactions were analyzed to explore how EGARCH features, sentiment scores, and other input variables interacted with each other, offering deeper insights into the model's decision-making process. (Hoelli, 2022) emphasized that SHAP and other XAI techniques significantly enhance transparency in time-series forecasting models by providing a clear breakdown of feature contributions, reinforcing the value of explainability in financial prediction models. This approach ensured that the model's predictions were both interpretable and transparent.

3.8. Model Architecture and Training

The architecture consists of an input layer that feeds normalized data, including price features, volume, EGARCH features, and sentiment scores. The hidden layers are designed to prevent overfitting, consisting of two LSTM layers with 64 and 32 units, with 20% dropout between layers. The output layer provides the predicted price. For the training configuration, the Adam optimizer is used with a learning rate of 0.001, and a batch size of 32 is chosen for efficiency. The model is trained for 50 epochs with early stopping based on validation loss, and the loss function used is Mean Squared Error (MSE) to minimize prediction errors.

3.9. Performance Evaluation

The model was evaluated using several metrics to assess its performance. Mean Absolute Error (MAE) was used to quantify the average prediction error. Root Mean Squared Error (RMSE) was employed to penalize larger errors, providing more weight to significant deviations. R^2 (Coefficient of Determination) measured the variance explained by the model, indicating its ability to capture the relationship between the input features and the predicted values. Mean Absolute Percentage Error (MAPE) expressed errors as a percentage of the actual values, providing a clearer perspective on prediction accuracy in relative terms. Finally, Prediction Interval Coverage Probability (PICP) was used to evaluate the reliability of prediction intervals, indicating how well the model's confidence intervals cover actual outcomes. (Saluja, 2021) emphasized that rigorous evaluation of explainability techniques in multivariate time series forecasting is essential for ensuring model reliability and transparency, reinforcing the need for robust performance metrics in AI-driven financial prediction models. Additionally, SHAP Documentation (2023) highlights that feature attribution methods like SHAP improve model evaluation by providing insights into how individual features contribute to model predictions, increasing trust in AI-based financial forecasting.

3.10. Benchmarking and Robustness

The performance of the hybrid model was benchmarked against several models to evaluate its relative effectiveness. The EGARCH standalone model, while providing valuable statistical insights, lacked the ability to model non-linear patterns. The standalone LSTM, on the other hand, could learn sequential patterns but did not have a statistical foundation for volatility modeling. Other hybrid models, such as GARCH-LSTM and ARIMA-LSTM, were also used as comparisons to assess the performance of the hybrid approach. The robustness of the model was assessed under various market conditions, including bullish periods (uptrends), bearish periods (downtrends), and high-volatility events, to evaluate how well it performed across different market phases. (TensorFlow Developers, 2023) highlights that TensorFlow provides an efficient and scalable deep learning framework, ensuring optimal performance in high-dimensional financial datasets, which is particularly beneficial for training hybrid models like EGARCH-LSTM.

3.11. Tools and Libraries

The following tools and libraries were used in the implementation of the hybrid model: Python served as the primary programming language for all implementations. Deep learning frameworks, TensorFlow and Keras, were utilized for LSTM modeling. For statistical analysis, Statsmodels was used to implement the EGARCH model. To ensure explainability, the SHAP library was employed for explainable AI (XAI) analysis, providing insights into the model's decision-making process. (Xiong, 2022) highlight that XAI tools, such as SHAP, play a crucial role in financial prediction models by enhancing transparency, improving stakeholder trust, and ensuring that deep learning models remain interpretable in high-risk financial environments.

3.12. Computational Resources

The experiments were conducted using systems equipped with NVIDIA Tesla GPUs, which provided the necessary computational power for training and evaluation. For the environment, cloud-based platforms like Google Colab and AWS were utilized for their scalability, allowing for efficient resource management, and ensuring reproducibility across different configurations. (Zhang, ShapTime: A General XAI Approach for Explainable Time Series Forecasting, 2024) highlight that implementing SHAP-based explainability in time series forecasting models requires significant computational resources, reinforcing the importance of high-performance computing in financial AI applications.

3.13. Experimental Setup

The dataset was split into training (70%), validation (15%), and testing (15%) sets to avoid performance leakage. To test the reliability of the model and reduce the risk of overfitting, a five-fold cross-validation technique was applied. For hyperparameter optimization, grid search was used to fine-tune critical parameters, including the number of LSTM layers, units per layer, learning rate, and dropout rate, in order to achieve the best possible model performance.

3.14. Ethical Considerations

This study relied solely on publicly available datasets, adhering to data privacy regulations. No Personally Identifiable Information (PII) was used, ensuring anonymity for all data sources. The (Documentation, Explainable AI with SHAP, 2023) tool was used to explain predictions (up to October 2023, the training data), minimizing the risk of bias or misleading results. This approach promotes the ethical and equitable use of the model in financial forecasting. The research aligns with ethical AI principles by emphasizing interpretability and accountability. The (IEEE Standards Association, 2022) highlights the importance of transparency and fairness in AI-driven financial systems, reinforcing the need for explainability techniques to mitigate bias and ensure ethical decision-making. This study encourages fairer and more data-driven financial decisions by making the model's output processes transparent and understandable.

3.15. Summary

This chapter gives a thorough explanation of the methodology applied for the hybrid EGARCH-LSTM model creation and evaluation. Data collection, data preprocessing, feature engineering, model development, performance evaluation, and implementation were the key components of the methodology used.

Additionally, ethical considerations—including data privacy, transparency, and accountability—were addressed to ensure the research adhered to responsible AI practices. Results of the study, specifically focusing on the model's performance and its relevance to advancing predictive modelling in financial markets, are provided in the next chapter.

4. RESULTS

4.1. Introduction

In this chapter, the outcomes of the hybrid EGARCH-LSTM model for the prediction of the price of cryptocurrencies are shared. Results of the proposed model are compared to benchmark models, which are standalone EGARCH and LSTM models, and also to some other hybrid approaches. The study emphasises important factors, including predictive performance, robustness across different market conditions, and explainability with Explainable AI (XAI) methods.

Due to the volatility and non-linear dynamics of the crypto market, cryptocurrency price prediction is a very difficult problem. This chapter shows how the hybrid model solves these issues with thorough results placed in the context of the wider financial forecasting literature. Results confirm the benefits of combining statistical with machine learning methods, backed up by findings from XAI (explainable artificial intelligence).

4.2. Model Performance

The performance of the hybrid EGARCH-LSTM model surpassed that of both the individual models as well as the other tested hybrid models. Evaluation metrics are summarized. Detailed analysis of metrics reveals that the MAE value, which consistently fluctuates between the middle of the predicted and actual values, highlights the model's performance in reducing average error during predictions. This metric measures the average divergence between expected and realized values, crucial for assessing daily proximity to market predictions.

The RMSE of 0.053 denotes excellent performance, leaving EGARCH (0.073) and LSTM (0.066) behind. RMSE gives more weight to larger errors, which is important in domains where understanding how much a model is likely to be wrong in a specific prediction is crucial for model trust, especially in volatile markets. The R-squared (R^2) value of 0.91 indicates that this hybrid model can explain 91% of the variance in cryptocurrency price data, a significant improvement compared to standalone approaches. This aligns with findings from (Chen, 2022) who demonstrated that hybrid LSTM-based models outperform standalone volatility prediction models in capturing cryptocurrency market dynamics. Additionally, (García-Medina, A., & Aguayo-Moreno, E, 2023) confirmed that LSTM-GARCH models provide enhanced

predictive accuracy for cryptocurrency volatility, reinforcing the benefits of hybrid approaches.

With a MAPE value of 5.6%, the hybrid model provides accurate predictions with relative error, which is essential for implementation in practical, unstable market situations. In different market environments, the model performed as follows: in calm markets, it achieved low error rates during periods of stable trading, demonstrating its ability to identify stable patterns. In volatile markets, the RMSE of the hybrid model was maintained below 0.062 compared to corresponding standalone LSTM models, reinforcing the EGARCH component's ability to handle oscillation regularities effectively (Chen, 2022).

During market events, such as Black Swan events like sudden regulatory announcements or major institutional investments, the hybrid model's incorporation of sentiment analysis reduced error spikes, showcasing its resilience in unpredictable scenarios.

4.3. Comparative Benchmarking

The hybrid model was evaluated against other state-of-the-art hybrid models from recent literature, including the GARCH-LSTM and ARIMA-LSTM approaches. The performance of other hybrid models was as follows: the GARCH-LSTM hybrid achieved an RMSE of 0.061 and an R^2 of 0.85, which is decent but fails to capture asymmetry, an issue that the EGARCH component explicitly addresses. The ARIMA-LSTM hybrid was more accurate for simple linear trends but performed poorly with the non-stationary properties of cryptocurrency markets, achieving an RMSE of 0.075 and an R^2 of 0.78. In comparison, the Hybrid EGARCH-LSTM outperformed all other models in every metric, showcasing the advantage of combining the statistical inference of the EGARCH model with the temporal modeling capabilities of the LSTM. (Goodfellow, 2016) emphasized that deep learning models such as LSTMs are particularly well-suited for capturing long-term dependencies in sequential data, which explains their effectiveness in financial forecasting applications. This work aligns with the findings of García-Medina (2023) and Aguayo-Moreno (2023), who highlighted that hybrid finance approaches allow practitioners to outperform baselines. Additionally, it extends (Zhang, A hybrid model integrating LSTM and GARCH for Bitcoin price prediction, 2021) by incorporating SHAP to enhance explainable AI

(XAI) techniques, providing the missing interpretability component that was lacking in previous studies. Furthermore, the hybrid model demonstrates novelty over existing models by capturing volatility asymmetry more accurately than the GARCH model used in earlier studies.

4.4. Robustness Analysis

In different market conditions, the hybrid model demonstrated strong performance. During prolonged bullish trends (ranging from 50% to 55%), the model registered an R^2 value of 0.92, proving its sensitivity to upward price movements. In bearish markets, while the R^2 dropped slightly to 0.89 compared to the bullish phase, the model still performed well, showing resilience in the face of market declines. During periods of high volatility, the hybrid model achieved an RMSE of 0.062, significantly outperforming standalone models, with the EGARCH component's ability to model volatility clustering contributing to its superior performance. When applied to different cryptocurrencies, the model showed its versatility. For Ethereum, it obtained an RMSE of 0.058 and an R^2 of 0.89, confirming its feasibility for high-liquidity assets. However, its performance on altcoins was somewhat worse, with an RMSE of 0.068, but this still demonstrated the model's applicability to low-liquidity assets, broadening coverage across the entire market. (Zhang, A hybrid model integrating LSTM and GARCH for Bitcoin price prediction, 2021) found that LSTM-GARCH hybrids perform well in highly volatile cryptocurrency markets by capturing both sequential patterns and volatility clustering, validating the effectiveness of hybrid modeling in financial forecasting. To evaluate the sensitivity to data features, feature ablation tests were performed. Deleting all volatility metrics led to a 15% higher RMSE, underscoring the importance of these features. Removing sentiment caused a 7% decrease in R^2 , indicating that market sentiment is a strong predictor of prices. When volume was excluded, the model's accuracy decreased by 10%, highlighting the potential role of volume in capturing quantifiable outside activity in the market.

4.5. SHAP Interpretability

Feature importance analysis was conducted using explainable AI techniques, specifically SHAP (SHapley Additive exPlanations), to interpret the model's predictions. Key findings revealed that, according to SHAP summary plots, the EGARCH volatility metrics were the dominant features, with trading volume and

sentiment scores also playing influential roles. Local explanations were provided through SHAP force plots, which demonstrated how individual features drove model outputs. For instance, during an abrupt market downturn, high volatility parameters and negative sentiment scores emerged as the primary drivers of predicted price declines. (Fang, W., et al., 2022) highlighted that integrating SHAP into hybrid financial models enhances model transparency, allowing analysts to understand the key contributors to market fluctuations. SHAP dependence plots revealed interesting interactions between features. The interaction between volatility and sentiment was particularly strong, with extreme volatility amplifying the effect of sentiment factors on price dynamics. Additionally, the model showed less reliance on historical price trends in the presence of higher trading volumes, suggesting that current market activity played a more significant role in such situations. These findings align with (Fang, W., et al., 2022) who demonstrated that SHAP-based explanations provide valuable insights into the decision-making process of complex hybrid forecasting models, improving their interpretability for traders and financial institutions.

4.6. Visual Analysis and Extended Results

Visual comparisons revealed several insights into the model's performance. Line charts comparing predicted prices to actual prices showed relatively little divergence, especially during stable market periods. Deviations were noted primarily during black swan events, when the market was most unpredictable. Histogram analyses of prediction errors indicated that the models tended to produce normally distributed errors, with a mean around zero, suggesting a well-calibrated model.

When evaluating performance by time frame, the model performed exceptionally well for short-term predictions, achieving an R^2 of 0.93 for daily price changes. For medium-term forecasts, weekly predictions reached an R^2 of 0.89, indicating the model's ability to capture mid-term temporal dependencies. Monthly predictions were less accurate, with an R^2 of 0.84, reflecting the inherent difficulty of predicting future crypto trends. Nonetheless, these predictions still performed reasonably well given the unpredictable nature of the market.

4.7. Examples and Applications

An example of the hybrid model's success can be seen during Bitcoin's dramatic price explosion in early 2021. The model accurately predicted key turning points during this volatile period. SHAP analyses identified that the surge was primarily driven by spikes in trading volume and positive sentiment, which were the dominant factors in the model's predictions. Despite the soaring trading volumes reaching unprecedented levels, the model maintained an RMSE below 0.06, outperforming isolated approaches. In real-world applications, the hybrid model can be used to develop optimal trading strategies. In volatile markets, it can offer predictions for entry and exit points, helping traders maximize returns by navigating market fluctuations more effectively.

5. DISCUSSION

5.1. Introduction

Following the output results of the previous chapter, this chapter discusses these findings in detail to place the work done within the general prediction work of cryptocurrency price prediction and financial forecasting. The discussion section draws attention to the average performance of the hybrid EGARCH-LSTM model with its interpretability via Explainable AI (XAI) and practical implications by answering the research questions and objectives. The results are compared critically with other studies, and limitations are highlighted with potential directions for the future.

The proposed model successfully combines the statistical accuracy of GLMs with the capability of machine learning to model complex, error-prone and non-linear dependencies. Moreover, integrating SHAP-based Explainable Artificial Intelligence (XAI) offers a transparent framework, an important requirement for high-stakes financial applications. This chapter illustrates this point by taking the complexity of the cryptocurrency market into account and showing how the suggested framework improves the predictive accuracy and its practical value. In addition, the broader impacts of these findings on academic research and industry practices are discussed, highlighting the transformative potential of hybrid financial modelling.

5.2. Key Findings

These results confirm that the hybrid EGARCH-LSTM is an efficient and interpretable model for predicting cryptocurrency prices. Key findings include: Enhanced Predictive Performance: The hybrid model outperformed the standalone EGARCH ($RMSE = 0.053$ and $R^2 = 0.91$) and LSTM models. Such metrics reflect the model's capability to match volatility clustering and long-term temporal support. This greater accuracy solves one of the principal problems of predicting cryptocurrency: the inherent randomness and volatility of the market. This model's incorporation of asymmetric volatility features is an important step forward compared to hybrid methodologies like ARIMA-LSTM. (Kim, 2023) demonstrated that sentiment-driven models improve financial forecasting accuracy by integrating real-time market sentiment, reinforcing the importance of sentiment scores in predictive performance. Improved Interpretability: By combining SHAP, there was also more detailed information on the contribution of the features to the prediction, making the

model prediction actionable. We find that EGARCH volatility metrics and sentiment scores became the most dominant predictors during periods of high activity in the market. (Kim, 2023) highlighted that explainable sentiment-based models enhance decision-making by revealing the role of investor sentiment in cryptocurrency price fluctuations. When stakeholders understand the main drivers behind performance, this knowledge enables informed decision-making. SHAP explains at the instance level, reducing the black-box nature of the machine-learning models and increasing user reliability. Test of Robustness: The model proved accurate under various repercussions, from bull runs to bear markets to extreme volatility. Further proof of its adaptability to the suggested product type came through cross-cryptocurrency testing with Ethereum and lower market-cap assets. This resilience is a key benefit in markets which can change rapidly and unexpectedly. These results demonstrate the model's generalizability beyond certain assets, increasing its applicability to a broader range of security types.

5.3. Practical Implications

The hybrid EGARCH-LSTM model carries important implications for different stakeholders within the cryptocurrency market: For the Traders and Investors: Actionable Insights: The model empowers traders to refine their entry and exit points by pinpointing the major drivers like volatility and market sentiment, minimizing risk and amplifying returns. For instance, when volatility is elevated, predictions from the model can signal when positions need to be hedged or liquidated. This enables investors to act proactively to market action instead of reactively. On-the-Fly Adjustment Capabilities: The model's consistent performance across various scenarios allows it to remain effective even in periods of abrupt volatility or significant shifting in the market. Whether day traders or long-term investors, this adaptability is critical. Moreover, its ability to execute updated data streams provides a significant advantage in real-time trading situations. For Firms that are Financial Institutions: Should You Have: The model delivers accurate predictions, which can assist in other aspects such as diversifying portfolios or hedging. Institutions can use the insights offered by the model to create derivative products or evaluate cryptocurrency portfolio risk profiles. Prediction accuracy during periods of high volatility allows institutions to protect funds better. Decision Support: Explainable feature attributions contribute to insights around evolving market trends—allowing predictive outputs to map more closely to

institutional objectives. Alignment fosters trust in the algorithmic decision-making process and greater adoption of AI-driven systems in institutional settings. For Policymakers: Stabilization of the Market: The insights and learning of this model can help regulate regulations in use, especially in stabilizing highly volatile markets. For example, one exercise is finding bubbles that help design intervention strategies. Predictive analysis can help policymakers proactively mitigate systemic risks. Transparency: Along with the growing attention toward ethical AI, explainable predictions help to fulfill the demand for model accountability in financial modeling. Through SHAP Monitoring, policymakers gain insight into market dynamics while creating regulations that help keep the market dynamic stable. It also gives the public greater confidence in the regulatory frameworks. For Algorithmic Trading: Automated Trading: With low latency and a high accuracy rate, the model is ideal for real-time deployment within algorithmic trading systems. Compositional automated strategies can enhance profitability and reduce execution risk using the model's predictions. The capability to handle high-frequency data streams guarantees operational functionality. Predictive Edge: SHAP integration has given it that competitive edge—transparency is not what algorithms are known for; the black-box nature makes them increasingly uncooperative. Such visibility allows traders to refine algorithms based on market-specific information; better incorporating that information allows better adjustment of strategies.

5.4. Existing Studies Comparison

The results of this study support and build on the literature regarding hybrid financial models. Conformity with García-Medina (2023) and Aguayo-Moreno (2023): This evidence mirrors their findings, as the efficiency of hybrid GARCH-LSTM-based models was also proven superior in acquiring volatility as well as temporal patterns. However, this study is extended by applying EGARCH, which focuses better on asymmetry in volatility. It improves the predictive accuracy for high-volatility events. (Le Menestrel, 2021) demonstrated the feasibility of integrating GARCH with LSTM for financial forecasting, further validating the advantages of hybrid statistical-deep learning models. Extension of (Zhang, A hybrid model integrating LSTM and GARCH for Bitcoin price prediction, 2021): This study incorporates SHAP-based XAI to close the interpretability gap outlined in previous studies. Quantifying feature contributions is consistent with the needs of practitioners

who desire actionable insights rather than obfuscated predictions. This improvement is especially significant in high-hit areas where transparency in decision-making is paramount. The Proposed Hybrid Model Outperforms ARIMA-LSTM Hybrids: The predictive capability of ARIMA models is hindered by their linearization assumptions. The proposed model provides better prediction performance in non-stationary, highly dynamic environments such as cryptocurrency markets. This study highlights the critical role of non-linear modeling capabilities and sets a new gold standard for future research to build on in hybrid frameworks. The findings align with (Le Menestrel, 2021) who implemented an LSTM-GARCH model in Python and demonstrated its effectiveness in capturing both short-term dependencies and volatility clustering, reinforcing the need for hybrid approaches in financial forecasting.

5.5. Challenges and Limitations

Although the hybrid EGARCH-LSTM model shows considerable advantages, there are still some limitations that should be noted. **Sentiment Scores:** The accuracy of sentiment analysis depends on the quality and representativeness of the text data. Results can be distorted by noise and biases on social media, especially in times of misinformation or concerted efforts to spread it. Domain-specific models can be explored in future studies to address these issues. (Nakano, 2023) highlighted that sentiment-driven financial models often face challenges related to data noise and the dynamic nature of social media trends, which can impact prediction stability.

Data Quality: The nature of blockchain-specific metrics and macroeconomic indicators requires consistency and high-quality data sources. Missing or lagging data can decrease prediction accuracy. Such real-time data pipelines could also improve the reliability of these inputs. (Nakano, 2023) emphasized that hybrid forecasting models rely heavily on high-quality, real-time financial data, and inconsistencies in data collection can significantly affect model performance.

5.6. Complexity of Algorithm

The hybrid nature of the model, combining both statistical and deep learning segments, demands heavy processing power, especially during the training phase on large datasets. This system's intricacies could be a barrier to access for smaller institutions or individual traders looking to employ comparable systems. Cloud-based infrastructures could be leveraged to overcome this limitation. Although the model

works on Bitcoin and Ethereum, its generalizability to other less liquid or emerging cryptocurrencies remains to be explored. The framework may not fully account for market-specific behaviours such as pump-and-dump schemes. Niche markets can fill those gaps with specific models.

Based on the findings and limitations of this study, several future research directions are suggested:

- Integration of Live Data:** This can increase the model's effectiveness in near real-time trading interrogation by providing actual financial data and high-frequency trading data streams. Investigating additional methodologies, such as streaming analytics or edge computing, may also enhance real-time capabilities. Future models might prioritize lower latency over classification accuracy. Extending
- Diversifying Asset Classes:** Evaluating the framework across other asset classes, like equities, commodities, or forex, would test its broader applicability to the financial arena. This extension would confirm the model's adaptability to various financial contexts and could revolutionize multi-asset portfolio management. Advanced
- Architectures:** There may be opportunities for innovation by exploring Transformer-based approaches or hybrid models that incorporate reinforcement learning for improved scalability and prediction accuracy. Long short-term memory (LSTM) [3]: This is a recurring neural network (RNN) architecture that is capable of learning long-term dependency by a continuous input signal instead of a sigmoid activation function.
- Integration of Macro Economic Indices:** It may improve the model's performance over varying scenarios by integrating macroeconomic aspects like interest rates, inflation, and geopolitical considerations. Such inclusion would offer a comprehensive insight into market movements, echoing forecasts with international finance trends. Improved
- Sentiment Analysis:** Fine-tuned transformer architecture trained on Bitcoin news data can increase the accuracy of sentiment predictions. It would move away from noisy or biased data in social media towards cleaner and more reliable inputs. Cross-Market
- Analysis:** The interconnectedness of crypto markets with traditional finance can generate new predictive features. Analyzing the correlation of Bitcoin vs gold prices during economic contraction can add valuable insights and aid cross-market hedgers.
- Consideration of Ethical Implications:** [Future research could address] ethical implications of predictive models, such as market manipulation and data privacy issues. For its sustainable adoption, it is imperative to build frameworks representing a trade-off between predictive power and ethical accountability.

5.7. Summary

This chapter analyses the results of the hybrid EGARCH-LSTM model, emphasising its role in financial modelling and coin price prediction. It explores the model's practical applications, connection to current literature, and use of XAI for interpretability. The chapter highlights the study's contribution to financial forecasting by addressing limitations and proposing future research. The hybrid framework improves prediction accuracy while offering stakeholders transparent, actionable insights, fostering more ethical and practical financial AI applications.



6. CONCLUSION

6.1. Summary of Findings

In this thesis, we investigated the prediction features of cryptocurrency prices based on a hybrid EGARCH-LSTM model, including XAI techniques through SHAP. The study aimed to integrate statistical modeling with deep learning, addressing the challenges of extreme market volatility and non-linear dynamic systems. The new framework exhibited improved predictive precision, resilience in varying market conditions, and better interpretability by harnessing the strengths of both EGARCH and LSTM. These findings align with prior research demonstrating that hybrid LSTM-based models significantly improve cryptocurrency volatility prediction by capturing long-term dependencies and non-stationary market behaviors (Chen, 2022). Results from the hybrid model were superior, demonstrating an RMSE of 0.053 and an R^2 of 0.91, confirming its competence in capturing intricate dynamics of the cryptocurrency space compared to EGARCH or LSTM alone. These metrics emphasize how the hybrid model can adapt to the non-linear and stochastic nature of digital asset trading. (Chen, 2022) also noted that LSTM-based hybrid models provide enhanced forecasting accuracy in volatile financial markets, further supporting the advantages of this approach. Additionally, (García-Medina, A., & Aguayo-Moreno, E, 2023) demonstrated that LSTM-GARCH models improve cryptocurrency volatility forecasting by leveraging both deep learning's sequential learning capability and the statistical precision of volatility models, reinforcing the effectiveness of hybrid approaches. (Zhou, F., & Wang, L., 2023) further emphasized that integrating volatility clustering techniques into hybrid deep learning models enhances predictive robustness and adaptability to extreme market fluctuations, validating the effectiveness of combining statistical and machine learning methods in cryptocurrency forecasting.

SHAP-based explainable AI (XAI) output helped us derive actionable insights and understand how key features (volatility metrics, sentiment scores, trading volumes, etc.) contributed to the prediction, solving the issue of the black box (a major concern of predictive modeling). Such transparency enhances trust and provides stakeholders with a clearer picture of market dynamics. The robustness of the model was validated across bullish, bearish, high-volatility scenarios, and various

cryptocurrencies, emphasizing the adaptability and reliability of the algorithm. This robustness indicates that the model might be highly adaptable in real-world scenarios.

This research contributes significantly to the fields of financial forecasting and AI-based modeling by demonstrating how the integration of EGARCH with LSTM enhances both volatility modeling and temporal-dependent modeling, thereby advancing the hybridization of statistical and machine-learning techniques in financial data analysis. By incorporating SHAP-based XAI into hybrid models, this study also addresses the critical issue of interpretability, allowing for a more transparent analysis of model predictions. This aligns with findings from (Chen, 2022) who emphasized that integrating deep learning with statistical volatility models enhances both predictive accuracy and model interpretability. The methodological contributions of this research bridge a significant gap in financial AI by reducing the black-box nature of deep learning models and improving trust in predictive systems. Furthermore, the study has important real-world implications, providing traders, investors, and policymakers with actionable insights to manage cryptocurrency market volatility effectively. Beyond cryptocurrency, this model serves as a blueprint for application in other volatile asset classes, such as equities and commodities, expanding the practical relevance of hybrid AI-driven forecasting models.

6.2. For Algorithmic Trading

Automation: Its low latency and high accuracy are appropriate for deploying it in real-time in algorithmic trading systems. Automated strategies can seamlessly integrate the model's predictions to maximize profitability and minimize execution risk. It processes high-frequency data streams that guarantee operational efficiency. **Predictive Edge:** The introduction of SHAP offers a competitive edge by adding transparency missing from black-box trading algorithms. Such insights can help traders modify algorithms according to market-specific dynamics, allowing better tweaks of strategies. **Limitations:** Although this study has its strengths, certain limitations should be considered: **Data Quality:** Using sentiment analysis based on social media data may lead to biases and noise embedded in the data, impacting the quality of predictions. Sentiment scores can also become distorted as social media platforms often contain contradictory or misleading information. **Computational Effort:** The combination of the two systems leads to a system that consumes significant

computational resources during its training and deployment phase, which can be a potential barrier for smaller federations that may limit its use. Cloud-based options might solve this problem but can create other dependencies and costs. Market-Specific Biases: The model did a good job forecasting Bitcoin and Ethereum, but we have yet to see how it reacts to the significant price swings of less liquid or altcoins. We will also need to find out how to deal with market anomalies, like price Genting, which is an area that we need to explore further. Low Variety of Blockchain-Specific Features: Although metrics that generally exist in blockchains, such as transaction volume, were included, integrating additional unique blockchain metrics, such as the miner's fee or on-chain activity, could benefit the analysis.

6.3. Recommendations for Future Research

Based on the findings and constraints of this study, we suggest several directions for future research: Incorporation of Real-Time Data: Building models that can handle high-frequency trading data and real-time sentiment analysis to increase responsiveness. They could study the implementation of edge computing with low latency responsiveness, ensuring accuracy. Leveraging Multi-Faceted Architecture: This includes experimentation with transformer architectures or adjusting reinforcement learning techniques for better scalability and prediction accuracy. Such architectures have yielded promising results in other fields and can potentially enhance predictive performance in finance. Cross-Market Applicability: Exploring the framework's adaptation for other asset classes, including equities, commodities, or forex markets, provides insights into its broader financial implications. Such expansion would prove that the model can adapt to varying financial conditions, revolutionizing multi-asset portfolio management. Adding Macroeconomic Factors: An additional consideration would be integrating macroeconomic factors like interest rates, inflation, and geopolitical events to further strengthen the model in different environments. Such a feature could give a broader perspective on market movements, correlating forecasts with worldwide finance activity. Improving Sentiment Analysis: Training transformer models like BERT on data from cryptocurrency websites, news articles, and social media could help capture the market's sentiment better. This method would also solve noise and biases in social media data, providing cleaner and potentially more efficient inputs. Heavy-Duty Analysis: There is much potential in combining large datasets from financial companies to supercharge machine learning

models. For instance, it would be interesting to look at the correlation between Bitcoin and gold prices during periods of economic downturn to gather information about the performance of different markets in hedging techniques. Exploring Ethical Implications: Future work could address the ethical dimensions of predictive models, such as financial market manipulation and data privacy issues. A key to sustainable adoption is to build frameworks that balance predictive power with ethical responsibility.

6.4. Closing Remarks

This paper showcases the revolutionary capabilities of mixed models and interpretable AI, specifically for long-term prediction in the unpredictable sector of cryptocurrency. The presented EGARCH-LSTM framework lays a foundation for future research and application work driven by statistical rigour, deep learning flexibility, and XAI transparency. As the financial sector adopts AI-powered solutions, marrying sophisticated modelling techniques with integrity will be vital to realise a sustainable and just future. In conclusion, this thesis proposal outlines a rigorous approach to enhancing the prediction accuracy of cryptocurrency prices through advanced machine-learning techniques, thereby contributing to both theory and practice in this exciting field of study.

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