GLADYS ALHERI TANKO

COMPARISON OF FUTURE BITCOIN PRICES AND ELEMENTS AFFECTING CRYPTO PRICES

UOK-2023

COMPARISON OF FUTURE BITCOIN PRICES AND ELEMENTS AFFECTING CRYPTO PRICES

A THESIS SUBMITTED TO THE INSTITUTE OF GRADUATE STUDIES
OF
UNIVERSITY OF KYRENIA

By
GLADYS ALHERI TANKO
K20210671

In Partial Fulfilment of the Requirements for the Degree of Master of Science
In
Big Data Analytics

KYRENIA, 2023

COMPARISON OF FUTURE BITCOIN PRICES AND ELEMENTS AFFECTING CRYPTO PRICES

A THESIS SUBMITTED TO THE INSTITUTE OF GRADUATE STUDIES
OF
UNIVERSITY OF KYRENIA

By
GLADYS ALHERI TANKO
K20210671

In Partial Fulfilment of the Requirements for the Degree of Master of Science
In
Big Data Analytics

KYRENIA, 2023

Gladys Alheri TANKO: COMPARISON OF FUTURE BITCOIN PRICES AND ELEMENTS AFFECTING CRYPTO PRICES.

Approval of Director of the Institute of Graduate Studies

Prof. Dr. CANDAN ÖZOĞUL

We certify this thesis is satisfactory for the award of the degree of Masters of Science in Big Data Analytics

Jury committee in charger

Prof. Dr. Semra ERBAŞ	Jury Chairperson, Department of Big Data Analytics, University of Kyrenia.
Asst. Prof. Dr. Seda KARATEKE	Department of Big Data Analytics, University of Kyrenia.
Prof. Dr. Metin ZONTUL	Supervisor, Department of Big Data Analytics, University of Kyrenia.

I confirm that the material contained in this work was acquired and delivered in accordance with ethical and intellectual standards. I further affirm that I have properly assigned and acknowledged any information and findings that are not unique to my work, in accordance with by these rules of conduct.

Name, Last name: Gladys Alheri TANKO

Signature: ________________________________

Date: ____________________________________

ACKNOWLEDGEMENTS

I want to thank my supervisor, Prof. Dr. Metin ZONTUL, as well as the head of department (Big Data Analytics) and all of my lecturers: Prof. Dr. Semra ERBAŞ, Asst. Prof. Dr. Seda KARATEKE, and Asst. Prof. Dr. Şahin YAŞAR, for their advice and knowledge that they shared with me while I was a student at University of Kyrenia.

I also want to express my gratitude to my fellow colleagues for their continuous support in seeing me through the completion of my master's degree.

Lastly, I want to express my gratitude to my family for their unwavering support and inspiration throughout my life.

Gladys Alheri TANKO

ABSTRACT

Cryptocurrencies, as the first global implementation of digital money technology, have brought about significant transformations in businesses, employment, and the transactions industry. Bitcoin, launched in 2008, stands as the pioneering digital currency and has experienced a surge in popularity. With its decentralized currency creation and transaction processing capabilities, Bitcoin offers a unique proposition. The goal of this research is to look at the factors that affect cryptocurrency pricing and compare the expected price of Bitcoin to its actual price during a 10-day period. The basic volatility of the cryptocurrency market makes showing Bitcoin's future price difficult, which gets worse by a number of contradictory long-term outlooks. To address this challenge, the study employs the Facebook Prophet algorithm and Long Short-Term Memory (LSTM) for time series forecast, utilizing a daily dataset obtained from reputable sources such as Investing.com, Ychart, or Yahoo Finance databases. To analyze how well the anticipated and real prices performed, key measurements such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (R^2) are utilized. Notably, the accuracy and precision measurements demonstrate that the LSTM model beats the FPM model. In order to help beginner traders and investors make better investment decisions, this research intends to provide them with a thorough grasp of the volatility characteristics of the crypto market as well as the numerous causes impacting price variations.

Keyword**:** Cryptocurrency, Bitcoin, Facebook Prophet Algorithm, Long Short-Term Memory, volatility.

ÖZET

Dijital para teknolojisinin ilk küresel uygulaması olan kripto para birimleri, işletmelerde, istihdamda ve işlem endüstrisinde önemli dönüşümler getirmiştir. 2008 yılında piyasaya sürülen Bitcoin, öncü dijital para birimi olarak duruyor ve popüleritesinde bir artış yaşadı. Merkezi olmayan para birimi oluşturma ve işlem işleme yetenekleri ile Bitcoin benzersiz bir teklif sunar. Bu araştırmanın amacı, kripto para fiyatlandırmasını etkileyen faktörlere bakmak ve Bitcoin'in beklenen fiyatını 10 günlük bir süre boyunca gerçek fiyatıyla karşılaştırmaktır. Kripto para piyasasının temel oynaklığı, Bitcoin'in gelecekteki fiyatını göstermeyi zorlaştırıyor ve bu, bir dizi çelişkili uzun vadeli görünümle daha da kötüleşiyor. Bu zorluğun üstesinden gelmek için çalışma, Investing.com, Ychart veya Yahoo Finance veritabanları gibi saygın kaynaklardan elde edilen günlük bir veri kümesini kullanarak zaman serisi tahmini için Facebook Prophet algoritmasını ve Uzun Kısa Süreli Belleği (LSTM) kullanır. Beklenen ve gerçek fiyatların ne kadar iyi performans gösterdiğini analiz etmek için Ortalama Mutlak Hata (MAE), Ortalama Hatanın Karekökü (RMSE), Ortalama Mutlak Yüzde Hatası (MAPE) ve Belirleme Katsayısı (R2) gibi temel ölçümler kullanılır. Özellikle doğruluk ve kesinlik ölçümleri, LSTM modelinin FPM modelini geride bıraktığını göstermektedir. Yeni başlayan tacirlerin ve yatırımcıların daha iyi yatırım kararları vermelerine yardımcı olmak için bu araştırma, onlara kripto piyasasının oynaklık özelliklerinin yanı sıra fiyat değişikliklerini etkileyen sayısız neden hakkında kapsamlı bir kavrayış sağlamayı amaçlamaktadır.

***Anahtar Kelime*:** Kripto para birimi, Bitcoin, Facebook Peygamber Algoritması, Uzun Kısa Süreli Bellek, volatilite.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

ADL	Autoregressive Distributed Lag
AML	Anti-Money Laundering
ARIMA	Auto Regressive Integrated Moving Average
BTC	Bitcoin
$\mathbf{R^2}$	Coefficient Of Determination
CPI	Consumer Price Index
DA	Directional Accuracy
DeFi	Decentralized Finance
EPU	Economy Policy And Uncertainty
ETH	Ethereum
EU	European Union
FBI	Federal Bureau Of Investigation
5AMLD	Fifth Anti-Money Laundering Directive
FCA	Financial Conduct Authority
FinCEN	Financial Crimes Enforcement Network
GPR	Geopolitical Risks
GRU	Gate Recurrent Unit
ICOs	Initial Coin Offerings
KYC	Know-Your-Customer
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MDA	Movement Direction Accuracy
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
NFT	Non-Fungible Tokens
OLS	Ordinary Least Squares
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RQ	Research Questions
SDAE	Stacking Denoising Auto-Encoders
SLR	Simple Linear Regression

SVM	Support Vector Machines
SVR	Support Vector Regression
TR	Thresholds Regression

CHAPTER 1
INTRODUCTION

The Background, issue, goal, significance, study limits, and a summary of the thesis are all included in this chapter.

1.1. Background of the Study

The field of finance has changed in recent years as digital tokens and creative monetary pathways, tools, and technologies have established innovative approaches for financial transactions and different investment sources. Due to the common perception that the financial system was unstable, electronic currency was first deployed in the 1980s, but it was not until past decade that it gave rise awareness to crypto currencies (Chen et al., 2022). A form of virtual currency referred to as cryptocurrency employs encryption to protect and validate transactions on a blockchain system. Cryptocurrencies, as opposed to conventional currency like the dollar ($) or Euro (€), are decentralized and run without the oversight of any centralized entities. This indicates that they can be exchanged freely all over the world and are not regulated by governments or financial institutions. Bitcoin (BTC) and ethereum (ETH) are the first two and most popular cryptocurrency of its kind. It is virtually hard to forge this digital currency because of its form of encryption which is a distributed ledger built using blockchain technology and constant active trades and transactions (Mukhopadhyay et al., 2016), based on the use of distributed ledger technology, its transaction processes are seen as being more trustworthy.

The first global use of digital money was in bitcoin crypto currencies, which have transformed businesses, employment, and the transactions industry. Since its launch in 2008/2009, electronic currencies, including Bitcoin, the first of all digital currencies, have grown in fame. The public transaction register known as the blockchain is a distributed, p2p network where payment transactions in the bitcoin system are stored (Chohan, 2017). Bitcoin offers decentralized currency creation and transaction processing. A highly computation-intensive technique used for bitcoin mining ensures the blockchain's validity by protecting duplicate purchasing and altering payments that have already been accepted (Zhang et al., 2019). Using the codename Satoshi Nakamoto, an individual or group of individuals designed Bitcoin in 2009. It was the original and most widely used decentralized coin. It runs on a decentralized system, so hubs or computers on the network rather than a centralized authority verify payments (Farell, 2015). The system employs a method known as blockchain, which is simply a digital ledger that stores all of the network's exchanges. Even though all exchanges on the block chain technology are publicly accessible, users are able to stay anonymous by using a nickname or a Bitcoin identity that is not associated with their actual identity, which makes the system more unique and encourages user privacy and confidentiality (Berentsen & Schar, 2018). It is also frequently referred to as "digital gold" since, like gold, its supply is finite, since there can only ever be 21, 000,000 bitcoins produced (Henriques & Sadorsky, 2018; Taskinsoy, 2021).

Blockchain technology utilized in cryptocurrency development is a public, immutable distributed registry that makes it seamless to record activities and oversee assets in a corporate network and it is still the foundation technology for all digital currencies, including Bitcoin (Pilkington, 2016). Each transaction is validated by the consensus of system members, who form a block that validates and allows transactions based on the preceding block (Yli-Huumo et al., 2016). The technology doesn't just apply to bitcoin and all other crypto currency; it has a large range of uses, including managing supply chains, electoral systems, and proof of identity. Blockchain technology offers these systems with accountability, privacy, and decentralization. Blockchain technology is groundbreaking because it allows parties to trust one another without the need for middlemen like financial institutions or agencies (Yaga et al., 2018). Since it larger dataset, Bitcoin is the most recognized cryptocurrency in the rapidly expanding field of cryptocurrencies, has distinctive qualities, and is anticipated to continue rising in popularity, bitcoin was chosen as the subject of this study's research.

1.2. Problem of Study

Bitcoin and other cryptocurrencies have transformed how the general public views monetary and financial activities. Companies are drawn to cryptocurrencies and investors because of their decentralized structure, special features like smart contracts, and finite supply. However, there are risks associated with every investment option, so traders and investors, especially newcomers, should exercise caution and do due diligence before taking any actions. One of the main issues in the cryptocurrency industry is that there is now no authority in place to deal with all issues that arise in all transactions. This is a drawback of cryptocurrencies (Amsyar et al., 2020). According to DeVon (2022), Over $2 trillion dollars was lost into the cryptocurrency space recently due to problems with market turmoil, regulatory changes, global economic circumstances, an increase in the federal interest rate or Consumer Price Index (CPI), and the failure of financial or crypto exchanges like Terra-Luna and FTX (Fu et al., 2022; Briola et al., 2022). These are some unseen problems that could occasionally affect the price of crypto currencies (Deniz & Teker, 2020).

According to a study done in Indonesia by Sukarno and Pujiyono, (2020), the lawful use of cryptocurrencies to replace traditional currencies as a form of payment can either not comply with certain rules or be conclusively demonstrated to do so. This can make cryptocurrencies a tool of crime based on their use as a form of payment, leading to unfavorable perceptions of their utility and being harmful to the state. Traditional ideas of financial management and centralized control have been severely tested by the advent of digital currencies like Bitcoin and Ethereum. Governments may find it difficult to track and regulate the use of these decentralized currencies since they operate independently of any central authority. Concerns about possible unlawful activities like money laundering, tax evasion, and terrorist funding, which governments frequently view as threats to national security and economic stability, are raised when there is no oversight (Riley, 2021). The difficulty for the government administration is to find equilibrium between maintaining monetary sustainability and national interest while also recognizing people's right to use and invest in cryptocurrencies. According to Salman and Tehseen (2022), centralizing and establishing limits are crucial for managing illegal activities resulting from the usage of cryptocurrency.

1.3. Aim of Study

The objectives of this study are to compare the forecasted price of bitcoin to the actual price within a 10-day timeframe and to look into the factors like market demand, regulatory issues, global economic conditions, hike in federal interest rate or Consumer Price Index (CPI) and financial or crypto exchange collapse that may affect the price of crypto currencies from time to time currencies. The motivation behind this research is based on the recent unclear event in the crypto currency space that has left many investors to lose over $2 trillion dollars in 2022. Due to ignorance, a great number of people have over the years lost their assets, so this study also intend to fill a knowledge vacuum in the crypto currency investment community by helping novice traders and investors understand what factors can cause price changes in the crypto market.

The purpose of this research will be explored through discussion of three main research questions, along with time series prediction utilizing Long Short-Term Memory (LSTM) and Facebook Prophet Model (FPM).

- **RQ1**: What are the main elements influencing market volatility in the realm of digital currencies?
- **RQ2**: Which nations, both developed and underdeveloped, have adopted and rejected cryptocurrency?
- **RQ3**: What laws have been passed to forbid the usage of crypto currencies illegally?

1.4. The Significance of Study

Several researches have been conducted to properly understand the relevance of cryptocurrency and the blockchain as a decentralised network for the future generation of financial system, data security, privacy, and confidentiality. Despite this, a lot of people and organizations are still concerned about the risk posed by this system, which has generated heated debate on a global scale due to the benefits and drawbacks it offers to each person and business. Increasing volatility, market capitalisation, and transactions are all positively correlated with the prevalence of bubbles across all cryptocurrencies, according to an experimental study by Enoksen et al. (2020).

The VIX-index (The Chicago Board Options Exchange Volatility Index) constantly shows negative links with the incidence of bubbles, but the EPU-index (Economy (E), Policy (P), and Uncertainty (U)) mostly displays positive relationships with bubbles. The danger in the US stock market, macroeconomic news, and the uncertainties surrounding economic policy were all verified to have a substantial impact on bitcoin volatility (Yin et al., 2021). This only indicates that there are factors influencing the volatility of digital currency that are unknown to many traders and investors.

Complexities still exist over how cryptocurrencies really behave. Its supply, demand, acceptance, efficiency, and infrastructure can be severely impacted by external variables like modifications to legislation, wars, or economy crashes, which can cause swings in their market value and price stability (Ramos et al., 2021). It is presumed that sole reliance on a financial analysis of the risks related to digital currencies is insufficient to fully understand the relationship between cyberattacks and the potential disruptive effects they can have on the functionality of cryptocurrencies due to the complex technical nature of blockchains (Marella et al., 2020). Thus there is always a need for more education and continued study in the field of cryptocurrencies.

For any intrigued person or entity, bridging the knowledge gap in the cryptocurrency world is essential, especially in relation to governmental regulations and factors that may influence market volatility. This study is significant to help novice traders and investors in understanding the events in the cryptocurrency world. It is crucial to be aware of any news, regulations, or policies that might affect the market as governments across the world struggle with how to regulate cryptocurrencies without taking away people's freedom to choose. Also, the cryptocurrency market may experience volatility due to elements including general economic conditions, technical breakthroughs, and investor mood. Investors and traders will be able to manage the constantly-evolving crypto market landscape if they are aware of and knowledgeable about these variables.

1.5. Drawbacks of Study

There are some limitations to this study that ought to be taken into account in future investigations. The limitations encountered in this study are twofold. Firstly, the need to compare data from different databases and develops Python code for both the Long Short-Term Memory (LSTM) model and the Facebook Prophet model. Secondly, there is the challenge of determining the specific factor that influences Bitcoin volatility during a given time period. These limitations include the complexities associated with reconciling disparate data sources and ensuring accurate coding implementation for the predictive models. Additionally, identifying and isolating the key factor contributing to Bitcoin volatility within a specific timeframe can be a complex task. These limitations should be acknowledged as they may impact the precision and comprehensiveness of the study's results.

1.6. Thesis Overview

The five-chapter of this research performs a review of the literature and an experimental investigation of the comparing of bitcoin's price and elements affecting crypto prices.

- The issue statement, purpose, importance, constraints, and an outline of the next chapters are described in chapter one, which also provides a brief background on the topic of the study.
- In the second chapter, every crucial feature of cryptocurrency is in-depthly examined, with a focus on relevant research and the theoretical framework.
- The third chapter entails a detailed description of the study's methodology and experiment, including its strategy, data collection method, and data analysis techniques, is provided.
- The fourth chapter discusses the research by outlining the findings and presenting them.
- The fifth and last chapter of the report, which presents the research’s conclusions and recommendations for further investigation.

CHAPTER TWO

THEORETICAL FRAMEWORK AND RELATED RESEARCHES

In-depth Overview of the study is provided in this chapter, which focuses on relevant research and theoretic basis.

2.1 Theoretical Framework

2.1.1 Overview of Digital Currency

Digital or virtual currency which is known as cryptocurrency uses cryptography algorithms for security and is not controlled or operated by any central entities. It was first applied when Satoshi Nakamoto, a person or group, created the cryptocurrency known as Bitcoin in 2009. Since then, cryptocurrencies have grown in awareness and given investors access to a new investment market (Todorov, 2017). The fifth and last chapter of the report, which presents the study's conclusions and recommendations for further investigation. The fundamental concept behind cryptocurrencies is decentralization.It does away with the requirement for a central organization or middleman to make transactions easier. Instead, a network of computers called nodes verifies and records transactions in a public ledger called the blockchain. This system makes transactions faster, cheaper, and more secure than traditional methods (Niranjanamurthy et al., 2018). Blockchain technology, a distributed system that keeps all transactions private, is the foundation of cryptocurrencies. The network nodes check each transaction, and after it has been approved, it is uploaded to the blockchain. Because the blockchain is freely accessible, everyone can view the transactions that are made (Chen et al, 2018).

The idea that cryptocurrencies offer anonymity as well as privacy is one of their most important benefits. Users of modern capital markets must reveal their identities in order to complete transactions. On the other side, people may preserve their privacy and stay anonymous when using cryptocurrencies. Because of their anonymity, cryptocurrencies are preferred by those who value their security and privacy (Bunjaku et al., 2017). Another advantage of cryptocurrencies is that they are global and operate without borders. Traditional financial systems are limited by geographical boundaries and regulations. Without paying expenses, virtual currencies may be transferred immediately and cheaply to any location in the world (Wronka, 2021). Cryptocurrencies do have certain difficulties, though. Cryptocurrencies are appealing to criminals for money laundering and other unlawful operations because they are unregulated and decentralized. Law enforcement organizations have found it difficult to follow illegal activities due to the anonymity of transactions and the inability to trace them (Kethineni & Cao, 2019; Jacquez, 2016). Moreover, cryptocurrency instability has been a cause for concern for investors. Cryptocurrency values can change drastically, sometimes even inside a single day. It has been tricky for cryptocurrencies to gain approval as a major asset class due to this instability (Bhatnagar et al., 2023).

The most popular cryptocurrency is Bitcoin, which has a market dominance of over 40%. It is followed by other popular cryptocurrencies like Ethereum, Binance Coin, Cardano, and Dogecoin (Mahdi et al., 2021). Each cryptocurrency has its unique attribute and use cases, and investors should research each one carefully before investing. Cryptocurrencies have boosted the development of new technologies and applications. New technology and applications have developed because to cryptocurrencies. Supply chain management, real estate, and other industries have all used blockchain technology. With the introduction of decentralized finance (DeFi), a new money system based on blockchain technology, financial services including lending, borrowing, and trading are now available without the use of middlemen (Andoni et al., 2019). In contrast to traditional banking systems, virtual currencies provide a number of benefits, including privacy, anonymity, and borderless transactions (Cousins et al., 2019). They face problems such as a lack of regulation, volatility, and criminal activity, though.Financial institutions and investors have a lot of interest in cryptocurrencies, which has inspired the creation of new applications and technologies. When choosing a cryptocurrency, shareholders should thoroughly study each one, just like they would with any other investment.

2.1.1.1 Challenges Associated With Crypto Currency

In recent years, cryptocurrencies' acceptance and use have increased. It is decentralized, meaning it is not under the control of a single authority like a government or financial institution, and usually employs encryption for security. Nonetheless, cryptocurrency raises a number of risksThere are a few issues with cryptocurrency, though. Cryptocurrencies are prone to security lapses and hacking assaults since they are housed in digital wallets. These attacks can cause a loss of money. However, if investors forget their passwords or lose access to their wallets, they risk losing all of their assets (Kim & Lee, 2018 Cryptocurrencies are known for their extreme price swings, with values sometimes fluctuating by considerable amounts within hours or days. This crazy price fluctuation behavior is one of the most significant risks connected with cryptocurrencies (Bratspies, 2018). Because of this instability, it is difficult to foresee price fluctuations, and investors who purchase and sell at the incorrect times risk suffering significant losses (Engle, 2004). Despite its rising use and popularity, there has been growing worry about the cryptocurrency industry's lack of controls (Wronka, 2021). Bitcoin laws are crucial for safeguarding investors and consumers, preserving market stability, and stopping criminal activity like fraud and money laundering.Regulations can provide a framework for cryptocurrency businesses to operate within and establish legal standards for the industry. Without proper regulations, the industry can be prone to volatility and instability, which can have negative impacts on investors and the economy (Khan & Hakami, 2021; Sotiropoulou & Guégan, 2017).

Digital currency usage for unlawful purposes, such as money laundering and financing terrorism, is the major cause for worry. Because virtual currencies are decentralized and anonymous, it may be difficult for authorities to monitor and track transactions, which draws criminals (Teichmann & Falker, 2020). By establishing know-your-customer (KYC) and anti-money laundering (AML) safeguards for bitcoin enterprises, regulators can help to lower these risks. Companies are obligated by KYC and AML standards to identify their clients and notify authorities of any suspicious conduct (Fanusie et al., 2018). By prohibiting market manipulation and fostering fair competition, regulations can also assist in the stabilization of the crypto market. The lack of regulations in the industry can make it susceptible to market abused, such as pump-and-dump techniques, which can cause significant price fluctuations and damage investor confidence (Austin, 2021). Regulations can prevent such activities by setting standards for market participants and by enforcing penalties for illegal activities (Kamps & Kleinberg, 2018).

In recent years, several countries have contemplated how to handle cryptocurrency. Several countries adopted a few regulatory strategies, some of which were more open than others. With its Payment Services Act, which establishes a legal framework for cryptocurrency exchanges, Japan, for instance, has been one of the most innovative nations in terms of cryptocurrency regulation (Wilson, 2019). Nevertheless, as part of a stricter regulation, trading in cryptocurrencies and initial coin offerings (ICOs) are forbidden in China (Bellavitis et al., 2021).Crypto currency regulations are necessary for protecting consumers, maintaining market stability, and preventing illegal activities and can help establish legal standards for the industry, mitigate risks, and promote fair competition. However, overregulation can hinder creativity and restrict the upside benefits of cryptocurrencies. Therefore, it is essential to find a balance between protecting safeguarding and promoting innovation (Chohan, 2021).

2.1.1.2 Benefits and Advantages of Crypto Currency

One of Bitcoin's most key properties, among many others, is its decentralized aspect. Unlike real currency, which is operated by governments and financial institutions, Bitcoin is decentralized, meaning it operates peer-to-peer with no central authority (Bunjaku et al., 2017). As a result, it is immune to governmental meddling or manipulation and is not affected by monetary policy-driven inflation or deflation. It is not governed by a single body or authority due to its decentralized nature, making it safer (Lu, 2022). Another key benefit of bitcoin is its total transparency and anonymity. Operations on the blockchain, the help to discover that enables most cryptocurrencies, are public and cannot be edited or deleted. Its openness makes it simpler to detect fraudulent acts and guarantees the security of transactions (Rajasekaran et al., 2022). At the same time, Bitcoin provides some privacy because users may make transactions without revealing their personal information. Those who value privacy and security will find it appealing (Herrera-Joancomart, 2015). This makes it attractive to individuals who value privacy and security (Herrera-Joancomartí, 2015).

Bitcoin is also simple to use, allowing anybody with an internet connection to join in its ecosystem (Chen, 2018). Bitcoin, unlike current financial systems, does not need users to have a bank account or a credit card. People who don’t have access to traditional banking systems will find it simpler to join in the world economy as a result of this accessibility (Abdulhakeem & Hu, 2021). Additionally, Bitcoin is extremely safe since it secures transactions with advanced encryption algorithms. The blockchain technology that supports most cryptocurrencies is almost hack-proof, and manipulating or altering the information stored on it is nearly difficult (Yao et al., 2019). As a result, Bitcoin provides a more dependable and private mode of payment, especially for online purchases (Zhang et al., 2019).The speed of bitcoin is another advantage. Credit scoring, document verification, and other administrative tasks can be time-consuming and cost with modern banking systems. These tasks can take many days, if not weeks, to perform and are costly. In comparison, cryptocurrency transactions are handled extremely immediately and at a small portion of the price of conventional banking systems (Peters & Panayi, 2016).Due to its usefulness, bitcoin is an ideal replacement for both companies and people trying to cut costs and time.

In addition to being extremely portable, cryptocurrency may be used for transactions from any location in the world. Cryptocurrency is a universal payment method that can be used for transactions anywhere in the world, unlike traditional money, which is subject to exchange rate changes and other limitations (Badea & Mungiu-Pupazan, 2021). Because of this, it is a desirable choice for people and companies who conduct business internationally. And last, investing in cryptocurrencies presents a special possibility. It offers a greater potential for development and profit than traditional investments because it is a more recent type of investment. Moreover, diversity is provided by bitcoin investments, which may help investors spread their risk and reduce losses (Xi et al., 2020A few features and benefits of Bitcoin include decentralization, transparency, privacy, access, safety, speed, mobility, and financial value. Cryptocurrency has the ability to change not just how users interact with one another and handle their money, but also the whole world's banking system, even though it is a new invention with its own set of difficulties. Future use and investment in digital currencies may result in further benefits and opportunities.

2.1.1.3 Block chain Technology

Blockchain technology is a database that has improved data storage and sharing. Due to its potential to have a great influence on different forms of industries, including banking, healthcare, supply chain management and others, blockchain technology has gained a lot of attention recently. A computer system or nodes, which work together to confirm and register network transactions, serves as the foundation of blockchain technology. Each block on the blockchain consists of a number of transactions, and a block cannot be changed or deleted after it has been added to the chain (Ahram et al., 2017).This produces an encrypt, open, and traceable record of all network transactions. Blockchain technology's important element is decentralization. Blockchain technology allows a network of users to interact to maintain and protect the network, compared to current centralized systems, which are managed by a single entity (Murray et al., 2022). Since there is no single point of weakness, the network is more resistant to threats and other sorts of manipulation. Another key aspect of blockchain technology is the use of cryptographic methods to ensure network security. Transactions on the blockchain are verified by complicated mathematical processes, making it almost difficult to change or fake transactions. As a result, blockchain technology delivers a high degree of anonymity and privacy, which is especially meaningful in areas such as banking and healthcare (Efanov & Roschin, 2018). Blockchain technology offers additional advantages in terms of usefulness and value for money in addition to security and decentralization.By erasing the need for middlemen such as banks or other financial entities, blockchain technology has the ability to greatly lessen cost of transaction and timeframes. This makes it a very interesting alternative for corporations and organizations that want huge quantities of value to be transferred rapidly and effectively (Singh et al, 2019). In terms of digital data exchange and storage, blockchain is an important improvement. Because of its decentralization, simplicity, and safety, it has the ability to totally change how we do business online.It is a preferred choice for many businesses. It will be interesting to watch what new applications and use instances arise as the technology grows and evolves.

2.1.1.4 Smart contract

Smart contracts are written computer programs that automatically carry out the terms and conditions or policies that a contract should follow. They may be carried out automatically anytime a number of predetermined conditions are satisfied since they are self-executing. By offering a safe and efficient method for solving critical transactions and deals, this cutting-edge technology has the ability to completely change the way business are conducted. Smart contracts are made safe, unchangeable, and resistant to outside influence using blockchain technology (Zheng et al., 2020). They can work in many different fields, such as handling supply chains, banking, and estate development. One of the most major benefits of smart contracts is that they eliminate the need for intermediaries such as attorneys or banks to authorize and enforce contract conditions. This lowers the possibility of fraud or human mistake while speeding up, costing less, and increasing transparency of transactions (Eenmaa-Dimitrieva & Schmidt-Kessen, 2019). Smart contracts' capacity to create a decentralized, secure, and effective environment for transactions and agreements has the ability to completely reshape the way we do business.

2.1.1.5 Solidity

The Ethereum blockchain uses the high-level programming language called Solidity that is use to write smart contracts. It is a statically typed language, meaning that variables must be identified with their data type before they are used. Solidity also supports inheritance, which allows for code reuse and reduces redundancy (Wohrer & Zdun, 2018). One important feature of Solidity is the use of pragmas. Pragmas are compiler instructions that tell the compiler how to handle the code being written. For example, the “pragma solidity” statement at the beginning of a Solidity file tells the compiler which version of the Solidity language to use. Pragmas are also used to enable or disable certain features or optimizations. For instance, the “pragma experimental ABIEncoderV2” statement enables the encoding and decoding of complex data types, while the pragma “solidity version” statement shows that the code should be compiled using certain solidity version (Signer, 2018). Overall, pragmas provide a way for developers to ensure their code is written in a specific way, and to take advantage of new features and optimizations as they become available in the Solidity language.

2.1.1.6 Bitcoin

Bitcoin is a decentralized digital currency, which runs independently without a central bank or administrator. It was developed in 2009 by an unidentified individual or group under the alias "Satoshi Nakamoto." Since its inception, Bitcoin has experienced a tumultuous history, marked by dramatic price fluctuations, regulatory scrutiny, and controversy (Todorov, 2017). The origins of Bitcoin can be traced back to a 2008 white paper authored by Satoshi Nakamoto titled "Bitcoin: A Peer-to-Peer Electronic Cash System." In the article, a decentralized electronic payment system based on cryptographic evidence rather than trust was developed. This system enables safe, direct transactions between people without the use of middlemen like banks or payment processors (Nakamoto, 2008). In January 2009, the Bitcoin network went live, and the first ever block of bitcoins was mined, known as the Genesis Block. The first known transaction involving Bitcoin took place later that same month, when Satoshi Nakamoto sent 10 bitcoins to a developer named Hal Finney (Wu & Wu, 2022). Bitcoin gained popularity over the following years, with its value rising from fractions of a cent to over $1,000 by 2013. This meteoric rise was due to a combination of factors, including growing adoption by merchants, media attention, and speculation by investors (Feinstein & Werbach, 2021).

However, Bitcoin's popularity also attracted regulatory scrutiny, with concerns raised about its potential use in money laundering and other unlawful activities. In 2013, the federal bureau of investigation (FBI) shut down the Silk Road, an online black market where Bitcoin was the primary payment method; further highlighting these concerns (Spagnoletti et al., 2021). In 2017, Bitcoin's value increased significantly once more, reaching a record high of about $20,000. This was due in part to increased mainstream adoption, with major companies such as Microsoft, Dell, and Expedia beginning to accept Bitcoin payments (Aysan et al., 2021). But this quick ascent was accompanied by a similarly spectacular fall, with the price of Bitcoin falling to about $3,000 by the beginning of 2019. According to Auer (2019), this fall was primarily caused by a confluence of regulatory uncertainty, hacking attacks, and the burst of the cryptocurrency bubble. Despite these difficulties, Bitcoin is still a popular and important cryptocurrency with a market value of over $1 trillion as of 2021. Numerous additional cryptocurrency and blockchain-based apps have also been developed as a result of it (Taskinsoy, 2021). Bitcoin's future is still up in the air because to continuous discussions over its governance, scalability, and regulation. The development of new kinds of decentralized digital currencies and blockchain-based applications has been made possible by its considerable impact on finance and technology.

2.1.1.7 Bitcoin Mining

The process of validating and adding up transactions from the network of bitcoins to the blockchain registry is known as bitcoin mining. To ensure validated transactions and get new Bitcoins as payment, miners utilize particular software to solve difficult mathematical tasks (Bamakan et al., 2020). As more people participate in mining, the difficulty of these equations increases, making it more challenging to earn Bitcoin rewards. While mining can be profitable for those with the right equipment and expertise, it also requires a significant investment of time, money, and energy. Furthermore, the energy use involved with mining of bitcoin has sparked concerns about its compound effects (Derks et al., 2018).

2.2 Related Studies

This section contains summaries of past studies on the factors and predictions for cryptocurrencies that are pertinent to this study.

2.2.1 Past Research on Crypto Currency Prediction and Factors

2.2.1.1 Past Studies on Crypto Currency Prediction

A unique mixed deep-learning model based on data segmentation is put forth by Li et al. (2022) with the goal of predicting price changes in the Bitcoin market and performing automated trading based on the outcomes of the predictions. The study's findings show that the suggested model performed better than other benchmark scenarios, such as machine-learning, econometric and deep-learning models. In a trading simulation, the suggested model outperformed both the buy and hold approach and all benchmark models in terms of the return on investment.

By combining unorganized information from financial media, Jakubik et al. (2022) look into how a deep machine learning model might be used to enhance Bitcoin price forecasts and trading. The research demonstrates that the suggested forecasting method achieves an out-of-time rate of return that is much greater than a buy-and-hold approach. The report also emphasizes how incorporating financial news and deep learning provides traders and investors with assistance for the commercialization of incomplete information in finance.

In order to estimate the value of bitcoin, Zhang et al. (2022) carried out research utilizing the deep learning integration approach (SDAE-B). In accordance with the prediction findings, the DA is 0.817, the RMSE is 131.643, and the MAPE of the SDAE-B forecast price is 0.016. It can effectively track the unpredictability and nonlinear properties of the bitcoin price and has greater accuracy and lower error when compared to the other two approaches (LSSVM and BP).

Because the Fbprophet model performs better than LSTM and ARIMA in terms of functionality and also avoids the issues that these models produce when evaluating bitcoin data, Rathore et al. (2022) used it as the main model. Due to seasonality in historical data, this study offers an approach for forecasting the price of bitcoin that does not only rely on the past. The findings indicate that, even after seasonal data was available, the general gap between projected and actual values is small compared to other models.

Zhang et al. (2022) investigated an LSTM-P neural network model to forecast the future prices of Bitcoin and gold in this study and then juxtaposed LSTM to the suggested framework (LSTM-P neural network model), using a historical price series of Bitcoin and gold from 9/11/2016 to 9/10/2021. In terms of precision as well as accuracy, the findings demonstrate that the LSTM-P model performs better than both the traditional LSTM models and other time series prediction models.

Luo et al (2022) create ensemble prediction models based on machine learning and multiscale analysis, taking into account the multiscale features of bitcoin price. The Bitcoin price series from 2017/11/24 to 2020/4/21 and 2020/4/22 to 2020/11/27 are chosen as the training and forecasting datasets, respectively. The experiments demonstrate that the ensemble models can reach an accuracy rate for predictions of 95.12%, outperforming the benchmark models, and that the suggested models are robust in both upward and negative market scenarios.

A GARCH (p,q) model is used by Papadimitriou et al. (2022) to calculate the conditional standard deviation and anticipate the severe swings of the Bitcoin spike. Support vector machines (SVM), a method for machine learning, were used for the forecasting process. With reference to spiking examples, the most accurate forecasting model achieved out-of-sample prediction accuracy of 79.17% and 87.43%, respectively.

Ansari and H. Y. (2018) concentrated on predicting the value behaviour of cryptographic forms of money using statistical techniques and machine learning algorithms. The purpose of this research is to provide scientists and business analysts with extra possibilities to check the parallels and discrepancies between typical monetary expenditures. In this work, a simple linear regression (SLR) model with a single-variable series of closing costs and a multiple linear regression (MLR) model with a multiple-variable series of quantities and prices are employed for forecasting. Different standards are evaluated, and the results demonstrate that the ARIMA model achieves the greatest degree of precision on our dataset, next followed by MLR and LSTM.

Ye et al (2022) propose an innovative ensemble deep learning model that forecasts Bitcoin's next thirty-minute prices using cost data, technical signals, and sentiment indexes, which incorporates two types of neural networks, known as gate recurrent unit (GRU) & long short-term memory (LSTM), with stacking ensemble modeling to demonstrate that the ensemble method has greater accuracy and may assist investors in making the right choice of investments than other conventional models. Because of the instantaneous dissemination of comments on social media, this article also employs social media texts as the source data of public sentiment rather than news sources. The sentiment indices were created using an oral statistical technique. The experimental findings reveal that the near-real time forecast outperforms the daily prediction, with a mean absolute error (MAE) that is 88.74%.

By utilizing novel machine learning techniques, Erfanian et al. (2022) seek to resolve the BTC price prediction problem within the framework of both macro and micro economics theories. The researchers test whether or not the macroeconomic, microeconomic, complex, and blockchain indicators based on economic theories can foresee the BTC price using support vector regression (SVR), ensemble learning, ordinary least squares (OLS) and multilayer perceptron (MLP). The results demonstrate that several technical indicators may accurately anticipate the short-term price of Bitcoin, supporting the reliability of technical analysis. Overall findings demonstrate that SVR outperforms other machine learning methods and conventional approaches.

Table 2.1: Past Studies on Crypto Currency Prediction in terms of models and metrics.

S/N	Reference	Model	Performance Measures
1.	Li et al (2022)	A bidirectional LSTM deep-learning model	MSE, RMSE,MAPE MAE, and directional accuracy (DA)
2.	Jakubik et al (2022)	Long Short Term Memory (LSTM) & random forest model	mean-square error (MSE), the root mean squared error (RMSE), Precision, Accuracy,
3.	Zhang et al (2022)	SDAE-B (stacking denoising autoencoders (SDAE) & bootstrap aggregation (Bagging))	mean absolute percentage error (MAPE), direction accuracy (DA), & root mean squared error (RMSE)
4.	Rathore et al (2022)	Fbprophet model	root mean squared error (RMSE)
5.	Zhang et al (2022)	LSTM-P neural network model	MSE, RMSE, R^2, MAPE.
6.	Luo et al (2022)	Ensemble model using deep learning method & multiscale analysis.	Accuracy
7.	Papadimitriou et al (2022)	support vector machine (SVM)	Non-spikes using Linear, RBF, Confusion matrix for spikes.
8.	Ansari & H Y (2018)	Linear regression, Multiple Linear Regression model (MLR), Long Short Term Memory (LSTM), ARIMA (Auto Regressive Integrated Moving average).	MAE, MSE, RMSE
9.	Ye et al (2022)	Neural networks model (gate recurrent unit (GRU) & long short-term memory (LSTM))	MSE, MAE, MAPE and sMAPE. movement direction accuracy

			(MDA)
10.	Erfanian et al (2022)	Ordinary least squares (OLS), multilayer perceptron (MLP), support vector regression (SVR), & Ensemble learning.	Pearson's R, R^2, and Root Mean Square Error (RMSE)

2.2.1.2 Past Studies on Factor That Influences the Crypto Currency Price.

With regard to variables linked to kind and nationality of uncertainty, examined time, connection horizon, and severe situations, Ben Nouir and Ben Haj Hamida (2023) explore how geopolitical risks (GPR) and economic policy uncertainty (EPU) effect Bitcoin fluctuation. The results of this analysis, which used data collected every month from August 2010 to September 2021 using the ARDL model and quantile regression, show that June 2014 is a significant date that signals a change in the analyzed relationship. Additionally, they demonstrate how many factors affect how closely the link between uncertainty and bitcoin volatility evolves. Bitcoin volatility is impacted by US uncertainty in the short term, whereas China's concern has more long-term repercussions.

Ullah et al. (2022) investigate the relationship among famous and governmental affiliations and fluctuation in bitcoin prices by applying cue utilization theory and signaling theory and utilizing data panels on bitcoin prices from Bloomberg between 1 November 2019 and 31 May 2021. The study's authors discover a strong positive correlation between upward movement in bitcoin values and supportive government and celebrity tweets. The results show that investors should carefully diversify their portfolio to maximize their risk-return relationship, even when endorsements from famous people may temporarily trigger a "exponential rise" in bitcoin prices.

In order to explain the correlation between the fluctuation of the Bitcoin price and the market concentration in pool mining, Jia & Li (2023) develop a straightforward model including the mining market structure. The mining pool considers the trade-off between undermining the network because of its market dominance and preserving adequate hash rate distributions from distributed miners. The author's findings demonstrate that a mining pool finds it most advantageous to be size-self-constrained while preserving a positive chance of undermining the network in equilibrium. The restricted market concentration in pooled mining thereby limits the swings in the price of bitcoin.

In Maiti (2022), the erratic link between bitcoin prices and overall energy usage is examined between November 2010 and October 2021. To determine the unidentified parameters that cause the system's shift in Bitcoin prices, an isolated thresholds regression (TR) model is used. Six phases of change are identified by the authorized TR model for fluctuations in the price of bitcoin. The investigation discovers that the influence on overall bitcoin use of energy on the value of bitcoin is highly significant in the higher regimes, i.e. the influence of total bitcoin energy usage on bitcoin prices is not consistent but beneficial.

The goal of Feng & Zhang (2023) is to demonstrate that the value of Bitcoin have remarkably strong predictive potential for actual exchange rates for currencies, both in-sample and out-of-sample, as a significant addition to managed fixed and managed floating rate exchange rate prediction. The authors explore both the autoregressive distributed lag (ADL) specification and the error correction specification for the exchange rate prediction model based on Bitcoin. For certain of the exchange rates, predictions based on both parameters surpass various benchmarks. Given the well-known difficulties in predicting exchange rates, the outcome is encouraging for players in the currency market.

How significant are the interest rates, price increases, and fluctuations in markets for projecting Bitcoin values, for example, is one of the open problems Basher & Sadorsky (2022) explore in their research. Do these factors relative importance alter over time? And are the key macroeconomic factors that influence gold prices the same as those that influence bitcoin pricing, by combining conventional logit econometric models with machine learning classifiers that are tree-based. The analysis of this study shows that random forests are more accurate at predicting Bitcoin and gold price directions than logit models, with bagging and random forests recording prediction accuracies of between 75% and 80% for five-day forecasts and greater than 85% for 10-day to 20-day forecasts. Furthermore, analytical indicators which point to some degree of market inefficiency are crucial for projecting the direction of the prices of Bitcoin and gold. Lastly, the importance of oil price volatility in forecasting Bitcoin and gold prices shows that Bitcoin can take the place of gold in a strategy to diversify this kind of volatility. Gold may be used as a hedging or diversity asset against hyperinflation since gold prices are more affected by inflation than Bitcoin prices.

Applying daily samples from January 2, 2018, to July 31, 2020, Yaya et al. (2022) explore the determination, earnings, and spillovers of volatility from the cryptocurrency market to the gold and silver markets. They use the fractional tenacity approach. The findings demonstrate substantial price persistence, with bitcoin exhibiting the highest volatility persistence and silver the lowest. The findings of multidimensional GARCH modeling using the CCCVARMA-GARCH model and other lesser variations show that while there are bi-directional volatility spillovers, there is no chance of returns spillover between the bitcoin and gold (or silver) market. To fully take advantage of the diversified benefit and limit risk to a minimum without compromising projected returns of their portfolio, authors proposed a proper portfolio management and hedging tactics on more gold and silver holdings.

During the COVID-19 epidemic, Salisu and Ogbonna (2021) carried out a test on the influence of news on the predictability of return volatility of the digital currency market. The GARCH MIDAS framework, which supports mixed data frequencies, is used since the authors of this study employ hourly data for cryptocurrencies and daily data for the news indicator. They confirmed the hypothesis that propaganda news caused by the COVID-19 epidemic raises cryptocurrency return volatility relative to the time before the pandemic. Additionally, they demonstrate that the news effects-based predictive model outperforms the benchmark (historical average) model in predicting return volatility.

The questions that Boido and Aliano (2022) are most interested in are: (a) Does the value of cryptocurrencies grows have an impact on the value of NTFs? (b) Does public opinion have an impact on the value of NTFs? To establish connections and find the solutions to our study concerns, authors use causality and spill-over analyses. The findings demonstrate that, with the exception of stable coins, NFTs exhibit distinctive dynamics that are not tied to nor hardly correlated with cryptocurrencies or media attention. Their findings imply that NFT in digital art provides a diversification potential.

Cevik et al. (2023) investigate the effects of the COVID-19 outbreak and the launch of Bitcoin futures on the returns and volatility of Bitcoin. According to the study, the introduction of Bitcoin futures has a (positive) influence on its returns on the spot market, but there is no discernible interaction for volatilities. Additionally, the epidemic does not appear to have an impact on Bitcoin's returns or volatility, which is consistent with the idea that Bitcoin is protected from certain changes in the world economy. Additionally, the author's studies show that Bitcoin spot prices outperform its futures.

Table 2.2: Past Studies on Factor That Influences The Crypto Currency Price.

S/N	Reference	Factors
1.	Ben Nouir & Ben Haj Hamida (2023)	Geopolitical Risks (GPR) & Economic Policy Uncertainty (EPU)
2.	Ullah et al (2022)	Celebrity Endorsements And Government Sentiments.
3.	Jia & li (2023)	Bitcoin mining pool
4.	Maiti (2022)	Bitcoin Energy Consumption
5.	Feng & zhang (2023)	Exchange rate
6.	Basher & sadorsky (2022)	Inflation and oil price volatility
7.	Yaya et al., 2022)	Portfolio spillovers
8.	Salisu & ogbonna (2021)	Negative/positive-induced news
9.	Boido & aliano (2022)	Public opinion and increase in the value of cryptocurrencies generally
10.	Cevik et al (2023)	Bitcoin futures

CHAPTER 3
METHODS AND EXPERIEMENT OF RESEARCH

The chapter discussed the methodology and experiment technique. It mostly contains the methods for the first phrase of this research, which is the prediction of bitcoin price and second phase which is looking into the real time events and factors that affected crypto price between 2018 to 2022.

3.1 Research Methodology

For the research's prediction phase, Facebook prophet model (FPM) and Long Short-Term Memory (LSTM) will be employed due to their credibility for time series predictions, Facebook Prophet is an open-source algorithm usually used for forecasting time series It is a software for forecasting time series data that applies an additive model to non-linear patterns including seasonality and the effects of holidays as well as yearly, monthly, and daily trends. The Facebook Core Data Science team created it. Prophet is intended to be a useful and effective method for predicting time series data at a large scale (Lawnik & Banasik, 2020). On the other hand, Long Short-Term Memory (LSTM) is also used as the second model, as it is a form of Recurrent Neural Network (RNN) that enables learning long-term connections and is used in many different applications, such as time series prediction, natural language processing, music composition, etc. (Toharudin et al., 2021; Haris et al., 2022).

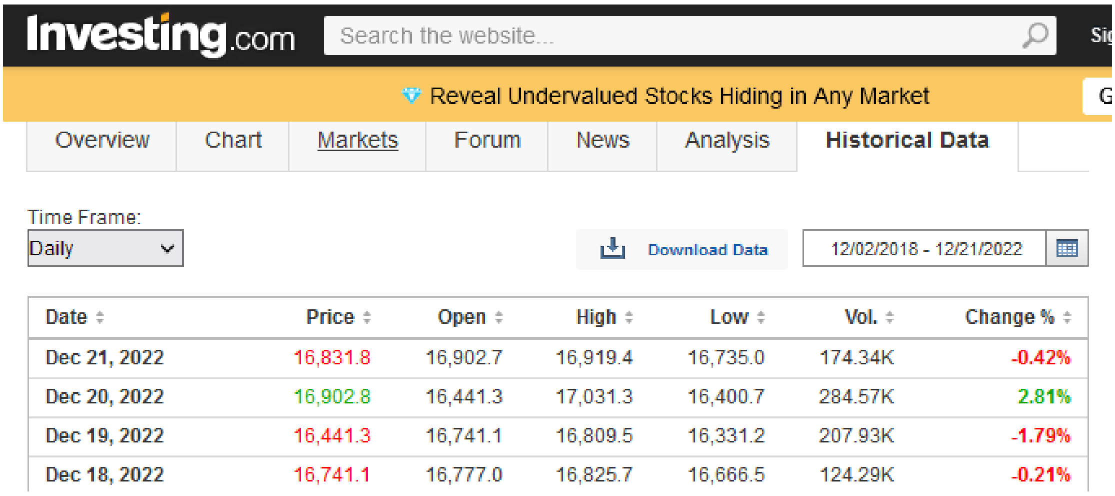
For the next phase of factors affecting crypto price volatility, this study looking into the real time events that affected crypto price between November 2018 to December 2022. A comprehensive literature review will be used to discuss the factors that influence bitcoin prices by looking back at earlier real time events in the crypto industry and comparing these events to the crypto price reaction at those particular times.

Figure 3.1: Bitcoin Downtrend from 68k -16k (Trading view)

For an instant, real time events that caused the drastic downtrend in the bitcoin market place as shown in Figure 3.1 above.

3.2 Data Collection and Pre-Processing

A time series dataset that includes a sequence of time stamps, such as hourly, daily, monthly, or weekly, is needed to be used for the bitcoin prediction.In this case, daily pricing data for bitcoin was acquired from one database (investing.com) and compared with identical data from another database during a five-year period (2018-2022),(Yahoo Finance database). This dataset contains information on the date, daily price, open price, high and low, price volume, and percentage change.



Investing.com
Search the website...
Reveal Undervalued Stocks Hiding in Any Market

Overview | Chart | Markets | Forum | News | Analysis | Historical Data

Time Frame: Daily
Download Data
12/02/2018 - 12/21/2022

Date	Price	Open	High	Low	Vol.	Change %
Dec 21, 2022	16,831.8	16,902.7	16,919.4	16,735.0	174.34K	-0.42%
Dec 20, 2022	16,902.8	16,441.3	17,031.3	16,400.7	284.57K	2.81%
Dec 19, 2022	16,441.3	16,741.1	16,809.5	16,331.2	207.93K	-1.79%
Dec 18, 2022	16,741.1	16,777.0	16,825.7	16,666.5	124.29K	-0.21%

Figure 3.1: Bitcoin dataset from investing.com

yahoo! finance
Search for news, symbols or companies

Finance Home | Watchlists | My Portfolio | Crypto | Yahoo Finance Plus | News | Screeners | Markets | Videos

Date	Open	High	Low	Close*	Adj Close**	Volume
Dec 21, 2022	16,904.53	16,916.80	16,755.91	16,817.54	16,817.54	14,882,945,045
Dec 20, 2022	16,441.79	17,012.98	16,427.87	16,906.30	16,906.30	22,722,096,615
Dec 19, 2022	16,759.04	16,807.53	16,398.14	16,439.68	16,439.68	17,221,074,814
Dec 18, 2022	16,795.61	16,815.39	16,697.82	16,757.98	16,757.98	10,924,354,698

Figure 3.3: Bitcoin dataset from Yahoo Finance database

Comparing the prices of Bitcoin on December 21, 2022, from investing.com and Yahoo Finance, we can see that there is a slight difference in the reported prices. According to investing.com, the price of Bitcoin on December 21, 2022, was $16,831.8, while according to Yahoo Finance, it was $16,817.54.

Table 3.1: Comparison of both database bitcoin price data.

Date	Investing.com	Yahoo Finance Database
Dec 21, 2022	16,831.8	16,817.54
Dec 20, 2022	16,902.8	16,906.30
Dec 19, 2022	16,441.3	16,439.68
Dec 18, 2022	16,741.1	16,757.98

Similarly, the reported prices on December 20, 2022, were $16,902.8 on investing.com and $16,906.30 on Yahoo Finance. On December 19, 2022, the reported prices were $16,441.3 on investing.com and $16,439.68 on Yahoo Finance. Finally, on December 18, 2022, the reported prices were $16,741.1 on investing.com and $16,757.98 on Yahoo Finance. The little price variation between the two sources can be attributed to market volatility and different reporting practices.

When implementing the Facebook Prophet model, it's crucial to keep in mind that the timestamps should be included in the "ds" column, while the projected values should be in the "y" column. These specific column names are necessary as the Prophet library expects them, and not having them could lead to errors (Patandung & Jatnika., 2021). However, the LSTM model does not have such requirements and can work with different column names for date and values.

	A	B
1	Date	Price
2	12/21/2022	16831.8
3	12/20/2022	16902.8

	A	B
1	Ds	y
2	12/21/2022	16831.8
3	12/20/2022	16902.8

Figure 3.4: Column change example.

Additionally, data normalization was used to preserve the price amount between 0 and 1. The method of machine learning usually makes use of the data preparation process known as data normalization. The normalization process is the process of scaling every column in a collection of data to the same value (Starovoitov & Golub, 2021). The code shown in Figure 3.5, below show the aspect of data normalization in both models.

```
# Read the data and normalize the 'Price' column
df = pd.read_csv('bitcoin - bitcoin.csv')
df['y'] = (df['Price'] - df['Price'].mean()) / df['Price'].std()
```

```
# Normalize the data using Min-Max scaling
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_y = scaler.fit_transform(y)
```

Figure 3.5: Data Normalization for both LSTM and FPM.

The data normalization equation (Starovoitov & Golub, 2021)

$$Xi = \frac{(x - x\_\{min\})}{(x\_\{max\} - x\_\{min\})} \quad (3.1)$$

This column arrangement can also be done during Facebook Prophet Model implementation as shown in the figure 3.6 and 3.7 below:

```
df = pd.read_csv('bitcoin - bitcoin.csv')
df
```

	Date	Price	Open	High	Low	Vol.	Change
0	12/21/2022	16831.8	16902.7	16919.4	16735.0	174.34K	-0.42
1	12/20/2022	16902.8	16441.3	17031.3	16400.7	284.57K	2.81

Figure 3.6: Data preview.

Using "`df.rename(columns={'Date': 'ds', 'Price': 'y'}, inplace=True)`" will also change the column name as Facebook Prophet Model calls for it.

```
df.rename(columns={'Date': 'ds', 'Price': 'y'}, inplace=True)
```

```
df
```

	ds	y	Open	High	Low	Vol.	Change
0	12/21/2022	16831.8	16902.7	16919.4	16735.0	174.34K	-0.42
1	12/20/2022	16902.8	16441.3	17031.3	16400.7	284.57K	2.81

Figure 3.7: Data Pre-process.

3.3 Experiment

The sub-section shows that prediction of bitcoin using Facebook model and LSTM (Long Short-Term Memory). The experiment will involve training the models on historical Bitcoin price data and evaluating their performance metrics in predicting future prices.

3.3.1. Facebook Prophet Model

Prophet on Facebook is a time series prediction tool, as was already mentioned. It depends on an additive framework that matches seasonal non-linear patterns on a yearly, daily, weekly, and holiday basis. For many different types of time series, including financial data, it may be utilized to create predictions. A historical Bitcoin price dataset was gathered and used to inform Prophet's price forecast. The data was collected and then processed for modeling. This experiment was carried out using the Google Colab IDE.

```
[ ]  !pip install pystan~=2.14
     !pip install fbprophet

     Looking in indexes: https://pypi
     Requirement already satisfied: p
     Requirement already satisfied: C
     Requirement already satisfied: n
```

Figure 3.8: Facebook Prophet Installation.

```
[ ]  import pandas as pd
     import warnings
     warnings.simplefilter(action='ignore', category=FutureWarning)
     from fbprophet import Prophet
     from fbprophet.diagnostics import cross_validation
     from fbprophet.diagnostics import performance_metrics
     from fbprophet.plot import plot_cross_validation_metric
     import itertools
```

Figure 3.9: Importation and Installation of other necessary libraries.

After installing Facebook Prophet, all other necessary libraries (including Pandas and fbprophet) were imported. To make predictions on the test set, the model was then invoked, fitted, and trained using the dataset. The predict function was then used to generate predictions for those periods. Predictions for future periods were calculated for ten (10) days using the make future dataframe method to build a new dataframe with ten (10) days' length of future periods.

```
model=Prophet()
model.fit(df)
```

```
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
<fbprophet.forecaster.Prophet at 0x7fb7020bb760>
```

```
m = Prophet(daily_seasonality = True, seasonality_prior_scale=0.1)
```

```
future = model.make_future_dataframe(periods=10)
```

```
forecast = model.predict(future)
```

```
forecast
```

Figure 3.10: Prophet Fitting, Training and Forecast.

```
forecast
```

ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper
2018-12-02	1454.451593	-1630.990363	6967.813389	1454.451593	1454.451593
2018-12-03	1490.150554	-2052.629416	6602.981715	1490.150554	1490.150554
2018-12-04	1525.849515	-2000.056427	6469.551849	1525.849515	1525.849515
2018-12-05	1561.548476	-2372.284274	6822.551175	1561.548476	1561.548476
2018-12-06	1597.247437	-2752.797152	6206.407989	1597.247437	1597.247437
...	...	...	...	...	...
2022-12-27	11050.890128	7038.369869	15727.827231	11050.890128	11050.890128
2022-12-28	10953.919938	6779.313894	15468.384542	10953.919938	10953.919938
2022-12-29	10856.949748	6988.539291	15735.575936	10856.949748	10856.949748

Figure 3.11: Forecast Results and Trends.

```
df_cv = cross_validation(model, initial='900 days', period='10 days', horizon = '10 days')
df_cv
```

```
INFO:fbprophet:Making 58 forecasts with cutoffs between 2021-05-20 00:00:00 and 2022-12-11 00:00:00
```

100% 58/58 [02:11<00:00, 2.67s/it]

	ds	yhat	yhat_lower	yhat_upper	y	cutoff
0	2021-05-21	55130.815870	52402.919821	57885.078178	37297.4	2021-05-20
1	2021-05-22	55221.561496	52650.741554	57876.114084	37448.3	2021-05-20
2	2021-05-23	55206.039025	52596.422464	57490.629986	34679.7	2021-05-20
3	2021-05-24	55361.193957	52751.941659	58148.925811	38750.6	2021-05-20
4	2021-05-25	55460.529335	52988.414786	58254.233358	38378.3	2021-05-20
...	...	...	...	...	...	...

Figure 3.12: Cross-validation

Figure 3.12 above shows the cross validation process for the prediction. Cross-validation is a resampling procedure used to evaluate a model through dividing the data into testing set and training set. The algorithm is analysed on the training set and then assessed on the testing set. To perform cross-validation in Prophet, you can use the cross_validation function, which takes the following attributes:

- Horizon (10 days): The amount of future days to be predicted.
- Initial (900 days): The amount of days that will be used as training data.
- Period (10 days): The amount of days in each fold of cross-validation.

This function will compute the forecast for each cross-validation fold and produce a data-frame containing both the actual (y) and predicted values (yhat). After this process, the model's performance was assessed using evaluation metrics function (such as mean squared error or mean absolute error) as seen in Figure 3.13 below.

```
df_p = performance_metrics(df_cv)
df_p
```

	horizon	mse	rmse	mae	mape	mdape	coverage
0	1 days	5.171520e+07	7191.328142	5809.069883	0.161583	0.148825	0.465517
1	2 days	6.086491e+07	7801.596667	6287.743347	0.174935	0.161603	0.413793
2	3 days	6.563862e+07	8101.766729	6430.820154	0.181393	0.189074	0.431034
3	4 days	6.246772e+07	7903.652079	6425.134659	0.183103	0.184074	0.379310
4	5 days	6.386151e+07	7991.339720	6517.271179	0.185291	0.163735	0.379310
5	6 days	7.191096e+07	8480.033081	6979.265593	0.198702	0.168733	0.327586
6	7 days	7.902681e+07	8889.702544	7387.620240	0.210751	0.206916	0.379310
7	8 days	9.294174e+07	9640.629389	7895.855262	0.223043	0.226110	0.310345
8	9 days	9.750363e+07	9874.392866	8158.294941	0.232550	0.220363	0.327586
9	10 days	9.008169e+07	9491.137440	7868.257901	0.224492	0.223108	0.327586

Figure 3.13: Daily forecast performance metrics

3.3.2. Long Short-Term Memory (LSTM)

Recurrent neural networks of a particular type called Long Short-Term Memory (LSTM) are very good at interpreting sequential data. Recurrent neural networks, specifically those of the LSTM variety, are highly adept at processing sequential data, in which current inputs are influenced by earlier ones. LSTMs address the vanishing gradient issue associated with conventional RNNs, and are capable of learning long-term dependencies via gates that regulate information flow (Güleryüz & Özden, 2020). LSTMs have been successfully applied to numerous time series forecasting tasks, including voice recognition, stock price prediction, and weather forecasting. The same historical Bitcoin price dataset used in the Facebook Prophet model was also used for prediction with the LSTM model, and the experiment was conducted using the Google Colab IDE.

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
df = pd.read_csv("bitcoin - bitcoin.csv")
y = df[['Price']]
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_y = scaler.fit_transform(y)
train_size = int(len(scaled_y) * 0.8)
test_size = len(scaled_y) - train_size
train_data, test_data = scaled_y[0:train_size,:], scaled_y[train_size:len(scalec
```

Figure 3.14: LSTM library and bitcoin data importation

The set of python code above in Figure 3.14, imports necessary libraries including numpy, pandas, sklearn, and keras to build a LSTM based deep learning algorithm to forecast Bitcoin prices. It loads the Bitcoin price dataset from a CSV file, selects the 'Price' column as the target variable, scales the data using MinMaxScaler, and splits it into training and test sets with an 80/20 split.

```
def create_dataset(data, lookback=1):
  X, Y = [], []
  for i in range(len(data)-lookback-1):
    a = data[i:(i+lookback), 0]
  X.append(a)
  Y.append(data[i + lookback, 0])
  return np.array(X), np.array(Y)
```

Figure 3.15: Function definition

Figure 3.15 above, defines a function called “create_dataset” that takes in two parameters: “data”, which is the input dataset, and “lookback”, which is an optional parameter set to 1 by default. The function creates two empty lists “X” and “Y”. It then loops over the range of the length of “data minus “lookback” minus 1, and for each iteration, it appends a slice of “data to “a of length “lookback”. It then appends “a” to “X” and “data[i + lookback, 0] ” to “Y”. Finally, it returns “X” and “Y” as NumPy arrays. This function is commonly used to create input-output pairs for time-series data, where “X contains the input sequences of length “lookback” and “Y” contains the corresponding output values.

```
lookback = 30
X_train, y_train = create_dataset(train_data, lookback)
X_test, y_test = create_dataset(test_data, lookback)
X_train = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1]))
X_test = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))
model = Sequential()
model.add(LSTM(50, input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(Dropout(0.2))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
grid_result = model.fit(X_train, y_train, epochs=100, batch_size=32, verbose=1)
y_pred = model.predict(X_test)
y_test = scaler.inverse_transform(y_test.reshape(-1, 1))
y_pred = scaler.inverse_transform(y_pred)
```

Figure 3.16: LSTM training and testing

Code shown in Figure 3.16 above, trains a LSTM model to make forecast based on time-series related data. The first two lines define a lookback window of 30 time steps and create training and testing datasets by calling the “create_dataset” function. Then, the training and testing data is reconfigured to meet the input form of the LSTM layer. The LSTM is then defined with 50 units, commence with a layer of dropout to prevent over-fitting and a dense output layer. The Adam optimizer and mean squared error loss are used to build the model. The model is then trained using the training set, with a batch size of 32 and 100 iterations. The testing data are then scaled back to their original values using the "scaler.inverse_transform" function before the trained model is used to generate predictions on them.

3.4 Comparison of Facebook Prophet and LSTM

Facebook Prophet and LSTM (Long Short-Term Memory) are two popular time series forecasting methods that have been widely used in various industries. Several factors can be considered when comparing Prophet and LSTM (Borges & Nascimento, 2022):

- **Accuracy:** LSTM generally outperforms Prophet when it comes to accuracy, especially for complex time series data with multiple inputs and outputs. However, Prophet can produce accurate forecasts for simpler time series data.
- **Interpretability:** Prophet provides more interpretability than LSTM, as it is based on certain statistical algorithms that allows for easy interpretation of the components of the model, such as trends and seasonality.
- **Ease of use:** Prophet is generally easier to use than LSTM, as it requires less data preprocessing and hyperparameter tuning. Prophet also has built-in features, such as automatic detection of seasonality, that make it easy to use for non-experts.
- **Scalability:** LSTM requires more computational resources than Prophet and can be slow to train on large datasets. Prophet, on the other hand, is designed to be scalable and can handle large datasets efficiently.

Using the factors stated above, Prophet is a good choice for simple time series forecasting tasks that require interpretability and ease of use, while LSTM is more suitable for complex time series data that require high accuracy and scalability (Triebe et al., 2021; Ouma et al., 2021). However, the choice between the two models ultimately depends on the specific requirements of the experiment.

3.5 Procedure

Sequential outline of the procedures involved in conducting the study:

i. A comprehensive assessment of prior studies associated to the chosen topic was conducted to enhance the understanding of the current study.
ii. The seminar course application form was submitted for approval.
iii. A synopsis of the study subject was given and submitted for review to the Big Data Analytics department.

iv. The report was put together and sent to the supervisor for evaluation and any required changes.

3.6 Research Timeline

In order to optimize the utilization of time and resources, it is typical for research projects to follow a study plan or timeline. This study started in February 2023 and concluded in September 2023. To facilitate a well-organized approach to thesis development, specific timeframes were allocated for each stage of the research. The detailed schedule for the thesis can be found in Table. 3.2 provided below:

Table 3.2: Research Timetable

Schedule	Duration (Weeks)
Previous Research Review	5
Proposal for thesis	4
Submission of proposals and comments	2
Data gathering	3
Data collection analysis and prediction	6
Compilation of the last chapters	5
Supervisor completed the final review.	2
Corrections and modifications	2
final correction and Jury	3
Total	**32**

CHAPTER 4
RESULTS AND DISCUSSION

This section highlights the research's findings on both the prediction of bitcoin price, the factors that affects the price and also answering two other questions about the adoption and laws of bitcoin use. This chapter explains the performance evaluation metrics and research questions.

4.1 Results

4.2 Performance Metrics.

To evaluate the model's prediction's reliability and efficiency, different measurement metrics must be adopted (Wang et al., 2020). Following the implementation of the bitcoin prediction, certain performance evaluation tasks were carried out to show how well the two models (FPM and LSTM) had done. In this study, the following prominent measurement metrics were used, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

```
MAPE:  0.12266305213736925
RMSE: 0.4420546309678972
MAE: 0.35453425586671755
R2: 0.9783442051902302
```

```
MAPE: 1.0
MAE: 0.14679232990603758
RMSE: 0.19564607062193662
R2: 0.14555417763833517
```

Figure 4.1: LSTM and FBM performance metrics respectively.

Table 4.1: Performance metrics for FPM and LSTM

Performance Metrics	FPM	LSTM
Mean Absolute Error (MAE)	0.427640977607584	0.35453425586671755
Root Mean Squared Error (RMSE)	0.5712212759165242	0.4420546309678972
Mean Absolute Percentage Error (MAPE)	1.0	0.12266305213736925
Coefficient of Determination (R^2)	0.4294405700560948	0.9783442051902302

This table above is showing the performance metrics measuring the accuracy of two models, FPM and LSTM, in making predictions. The four metrics are used to assess accuracy are Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (R^2).

- MAE measures the average size of the errors between expected values and the actual values. It is determined by summing the absolute difference between the expected and actual values and then averaging these differences. In this case, the MAE for the FPM model is 0.4276 (42.76%) and the MAE for the LSTM model is 0.3545(35.45%), suggesting that LSTM model performs slightly better in terms of average prediction error compared to FPM model.
- RMSE measures the square root average of the squared gaps between the expected and actual values. It lends more significance to high errors since it is calculated by taking the square of the errors. In this case, the RMSE for the FPM model is 0.5712 (57.12%) and the RMSE for the LSTM model is 0.4421 (44.21%). Again, LSTM model performs better compared to FPM model in terms of prediction accuracy because it is lower.
- MAPE measures the average percentage difference between the expected and actual values. It is useful for understanding the relative error of the predictions. In this case, the MAPE for the FPM model is 1.0 (100%) and the MAPE for the LSTM model is 0.1227 (12.27%), indicting much better relative performance.
- Coefficient of Determination (R^2) measures the proportion of the variance in the dependant target that is predictable from the independent features in the model. It represents the fitness of the model. In this case, the R^2 for the FPM model is 0.4294 (42.94%) and the R^2 for the LSTM model is 0.9783 (97.83%). The LSTM model with higher R^2 value shows that it accounts for a greater share of the variation in the target variable, suggesting that it has a better fit to the data.

The comparison between FPM and LSTM models reveals significantly different performance outcomes when evaluated using MAE, RMSE, MAPE and R^2 metrics. Specifically; the LSTM model seems consistently more accurate than its FPM counterpart. While it's important to note the difference between MAE, RMSE, MAPE and R^2 figures within LSTMs' predictions; implying an even distribution across error margin for forecasting. Complexity differences between models are naturally pertinent (as previously detailed in Chapter 3 (3.4)) - however it's equally worth noting other potential drivers affecting accuracy such as prohibitive problem complexities, data quality or model limitations. Further testing using a number of different feature engineering techniques and machine learning algorithms is needed to fully explore optimal approaches to forecasting bitcoin prices.

Table 4.2: Performance Equation (Seda Karateke et al., 2021; Coskuner et al., 2020)

Metrics	Equations	
MAE	$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left\|Actual_i - Predicted_i\right\|$$	(4.1)
RMSE	$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Actual_i - Predicted_i)^2}{N}}$$	(4.2)
MAPE	$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\|\frac{Actual_i - Predicted_i}{Actual_i}\right\| \text{ x } 100$$	(4.3)
Coefficient of Determination (R^2)	$$R2 = 1 - \left\|\frac{\sum_{i=1}^{N}(Actual_i - Predicted_i)^2}{\sum_{i=1}^{N}(Actual_i - mean(actual)_i)^2}\right\|$$	(4.4)

Table 4.3: Models hyper parameters

Models	Hyper Parameter	Value
FPM	Initial	900
	Period	10
	Horizon	10
	Daily. Seasonality	TRUE
LSTM	Epochs	100
	Batch Size	32
	Lookback	30
	Number of LSTM units	50
	Verbose	1
	Dropout	0.02
	Dense	1
	Optimizer	Adam

The table 4.3 above describes the first set of hyper parameters belongs to the FPM model, which includes an initial value of 900, a period of 10, a horizon of 10, and daily seasonality set to true. While the second set of hyperparameters belongs to the LSTM model, which includes a batch size of 32, 100 epochs, a lookback of 30, 50 LSTM units, a dropout rate of 0.02, 1 dense layer, and the Adam optimizer.

4.3 Elements Influencing Market Volatility in the Realm of Digital Currencies.

The crypto market is highly unstable, and several factors can influence this volatility. As stated in chapter 2(2.2(2.2.1(b))), these factor created in real life events can cause uncertainty and volatility in the crypto currency market. Firstly, According to Ben Nouir & Ben Haj Hamida (2023) and Jia & Li (2023), Bitcoin mining pool, economic policy uncertainty (EPU) and geopolitical risks (GPR) can significantly affect cryptocurrency market volatility. For example, the outbreak of COVID-19 in early 2020 caused significant uncertainty in the global economy, which led to a sharp decline in stock markets and other asset classes, including cryptocurrencies. Also, in 2021, China cracked down on cryptocurrency mining and trading, causing a fast sell in the value of Bitcoin, ethereum and other cryptocurrencies. Another factor is based on Celebrity Endorsements and Government Sentiments, Ullah et al (2022) suggest that celebrity endorsements and government sentiments can affect the cryptocurrency market's volatility. When influential celebrities endorse cryptocurrencies, the market tends to experience a sudden surge in demand and prices. Among the most notable cases was in 2021 when Tesla CEO Elon Musk tweeted about Dogecoin, causing the cryptocurrency to experience significant price fluctuations.

The energy required for bitcoin mining has also been noted as a crucial element impacting the volatility of the cryptocurrency market. According to Maiti (2022), the high energy consumption required for bitcoin mining can lead to environmental concerns and regulation, which can impact market value, such as Elon Musk's tweet on May 12, 2021, stating that Tesla would cease to accept Bitcoin as payment for its electric automobiles based on worries about the bitcoin's energy consumption. The announcement that a high profile corporation is severing ties with Bitcoin has sent shockwaves through the financial world causing significant drops in its value and that of related cryptocurrencies. As experts scramble to evaluate the effect of this sudden move on the larger market investors are bracing themselves for potential fallout. Another element is the conversion rate. According to Feng and Zhang (2023), the exchange rate between fiat currencies and cryptocurrencies can alter market demand and supply, hence influencing market value. Further, Basher & Sadorsky (2022) contend that rising commodity prices, such as those for oil, might result in inflation, which can have an effect on the buying power of fiat currencies and, consequently, on the value of cryptocurrencies. For instance, there were worries about growing inflation in the United States throughout the first half of 2021. The outcome was a widespread selloff of stocks and other customary investments. In response certain investors sought security from inflation by turning to cryptocurrencies. As a result the crypto market became more erratic and unpredictable. It should also be noted that oil price movements frequently influence broader financial markets.

Finally, there are some other factors like portfolio spillovers, negative/positive-induced news, public opinion, and increases in the value of cryptocurrencies generally, as well as the introduction of Bitcoin futures that can cause instability in the cryptocurrency trade (Yaya et al., 2022; Salisu & Ogbonna, 2021; Boido & Aliano, 2022; Cevik et al., 2023). One example of portfolio spillovers affecting the cryptocurrency market was the sell-off that occurred in early 2018, when many investors in traditional stocks and bonds began to liquidate their holdings due to concerns about rising interest rates and inflation. As a result, investors sold off their cryptocurrency holdings to make up for their losses in other asset classes, which greatly lowered the price of cryptocurrencies, including Bitcoin (Bouri et al., 2018). The cryptocurrency market has been incredibly unstable as a result of negative news stories about governmental crackdowns, security breaches, and fraud allegations. For example, in 2018 the announcement that cryptocurrency trading would be banned in South Korea triggered a roughly 20% decline in the price of Bitcoin in a single day (Shi & Shi, 2019). On the other side, good news stories, like the declaration of big corporate investments in Bitcoin, have also resulted in sizable market swings. For instance, Bitcoin's value increased by more than 15% in a matter of hours after Tesla revealed their $1.5 billion investment in the cryptocurrency in the beginning of 2021 (Isidore, 2021). The swings of the bitcoin market has also been influenced by public opinion. In this regard, the market may be greatly affected when famous people like Elon Musk or Mark Cuban talk about cryptocurrencies on social media.It is apparent that Elon Musks tweets concerning Bitcoin and Dogecoin carry a significant influence that leads to a general increase. Rise in the value of cryptocurrencies has also had an influence on the market's volatility. As more people have been interested in cryptocurrency investment, the market has become more unstable, with large price swings occurring often. Last but not least, the launch of Bitcoin futures contracts on significant exchanges has significantly increased market volatility. Futures contracts provide investors with the chance to make forecast on the future price of bitcoin, which may cause major market moves as investors take positions and rebalance their portfolios. Conclusion: The crypto market may see tremendous volatility because investors may become more cautious and risk-averse as a result of any events that induce uncertainty, panic, or geopolitical dangers.

4.4 Adoption of Crypto currency In the Categories of Developed and Underdeveloped Countries.

Since their start, cryptocurrencies have created debate. Some governments have accepted them wholeheartedly, while others have been more fearful. Adoption rates differ between developing nations and developed nations. The US, Japan, and the UK are among the developed nations that have lately shown interest in cryptocurrency. There are several important cryptocurrency markets in the US, and more investors and businesses, like Tesla, are embracing Bitcoin. Furthermore, the US government has been working on developing cryptocurrency laws (as stated by Mironeanu et al. in 2021). Japan is likewise recognized for its pro-crypto stance. In 2017, it was the first country to accept Bitcoin as a legitimate form of payment. This action promoted the use of cryptocurrencies and helped to legitimize them. In addition, Japan has put policies in place to safeguard consumers and stop money laundering (Mazikana, 2018). Another industrialized nation that has expressed interest in cryptocurrency is the United Kingdom. The Financial Conduct Authority (FCA), the country's financial control, has been actively working on legislation to offer clarity to firms dealing with bitcoin (Omarova, 2020).Additionally, a small number of companies in the nation, including bars and cafés, let consumers pay with Bitcoin.

On the other hand, underdeveloped countries like Nigeria, Venezuela, and Zimbabwe have also embraced cryptocurrencies due to their unstable economies and volatile currencies. Cryptocurrencies offer a decentralized and more stable alternative to fiat currencies that are subject to inflation and political instability. One example is Venezuela, which has been experiencing inflationary pressure and economy collapse. Due to this, many Venezuelans have resorted to digital currency as a way to protect their money (Rosales, 2019). In fact, the country launched its own cryptocurrency, the Petro, in an effort to bypass U.S. sanctions and stabilize its economy. Nigeria is yet another example, which has among Africa's highest adoption rates for cryptocurrencies. The big population, rising interest in cryptocurrencies as a method of financial inclusion, and government restrictions on cryptocurrencies are the main causes of this (Platt et al., 2022). As a result, people have discovered ways to trade cryptocurrencies illegally. The adoption of cryptocurrency varies significantly between developed and underdeveloped countries. While undeveloped nations have shown interest in cryptocurrencies, wealthy nations have traditionally been more open to them, especially when there are economic or political difficulties.

4.5 Laws Guiding the Illegally Usage of Crypto Currencies.

Money laundering, terrorism funding, and other financial crimes have increased as the use of bitcoin has grown in number. To solve this issue, governments all around the globe have enforced laws and regulations to prevent bitcoin from being misused. The USA Patriot Act is one of the most well-known laws focused at stopping illegal bitcoin activities. This rule requires the implementation of anti-money laundering (AML) practices, including those concerning the use of bitcoin. This improves the openness and transparency of bitcoin payments, making it difficult for criminals to make use of them. Overall, legislation like as the USA Patriot Act is critical to preventing bitcoin misuse and protecting the financial system's integrity. Governments may promote responsible crypto currency usage while simultaneously preventing financial crimes by introducing AML standards and other regulatory frameworks. The FinCEN (Financial Crimes Enforcement Network) has also provided cryptocurrency-related policies, showing that crypto currency exchanges and other firms must register and comply with know-your-customer (KYC) and Anti-money laundering (AML) rules (Dolar & Shughart, 2012). Other nations have published their rules and regulations in addition to the United States Patriot Act. A particular set of regulations for cryptocurrencies and virtual assets is the Fifth Anti-Money Laundering Directive (5AMLD) of the European Union (EU), which requires businesses to submit to Anti-money laundering (AML) and Know your customer (KYC) checks and report suspicious transactions (Pavlidis, 2020).

In addition, several nations have regulations that make the usage of digital currency for unlawful reasons such as tax evasion, and terrorism funding illegal. While cryptocurrency exchanges in Japan are governed by the Payment Services Act and the Act on Prevention of Transfer of Criminal Proceeds, the Proceeds of Crime Act of 2002 and the Terrorism Act of 2000 have provisions relating to cryptocurrencies (Barton, 2005). The use of cryptocurrencies is completely outlawed in other nations, like China, with severe penalties applied to individuals and businesses that violate the law. It is vital to understand that laws and rules governing cryptocurrencies differ widely by jurisdiction, and it is the responsibility of individuals and businesses that use cryptocurrencies to make sure that they are in compliance with all relevant rules and laws. Contribute support cryptocurrencies' long-term sustainability as a viable method of payment and investment. The regulations governing the illegal use of cryptocurrencies are intended to prevent financial crimes, increase transparency, and safeguard consumers. These rules are comparable to other regulations put in place to ensure that financial transactions are handled professionally and truthfully. To prevent legal problems and ensure the continuous existence of digital currency as a trustworthy form of transaction and investment, individuals and businesses must be aware of and abide by these rules. By following the rules and promoting responsible cryptocurrency use, people and organizations may help prevent illegal activities like money laundering and the sponsorship of terrorism. To summarize, knowing and adhering to regulations governing the usage of cryptocurrencies is critical for encouraging their use. The safe and proper usage of these digital assets. Both individuals and businesses may contribute to the legitimacy and continuing expansion of bitcoin as a legitimate financial tool by doing so.

4.6 Discussion

Performance metrics are essential for assessing the accuracy of models, algorithms, and systems across a range of disciplines. Performance metrics are used in the context of digital currencies to evaluate the models predicting accuracy that examine the variables influencing market volatility. In terms of MAE, RMSE, MAPE and R^2, the LSTM model exceeds the FPM model, according to section 4.2. It is crucial to remember, however, that performance metrics alone cannot provide an accurate picture of a model's total performance. They can be used with qualitative analysis and other metrics in future investigations (Tüzen et al., 2018). In both developed and developing nations, a number of variables affect the adoption of cryptocurrencies. Financial innovation, decentralization, and investment potential encourage cryptocurrency acceptance in developed countries. Whereas the popularity of cryptocurrencies in developing nations is driven by economic insecurity, hyperinflation, and a lack of access to financial services. In addition, the rules and regulations that regulate unlawful cryptocurrency use have a considerable influence on digital currency market volatility. Bitcoin has been used for unlawful purposes including finance laundering and terrorism funding. As a result, it's vital to include all of these elements when evaluating the efficacy of models that investigate the causes influencing market volatility in the digital currency industry.

CHAPTER 5
CONCLUSION AND RECOMMENDATION

Based on the findings of the performed research, this chapter gives the study's conclusion and recommendations.

5.1 Conclusion

To conclude, accurately forecasting the future price of Bitcoin is a challenging endeavor given the multitude of factors that impact cryptocurrency valuations. The intricate nature of these influences contributes to the complexity of making confident predictions. Bitcoin, being a decentralized digital currency, is susceptible to a range of elements such as geopolitical risks (GPR) and economic policy uncertainty (EPU), Celebrity Endorsements and Government Sentiments, Bitcoin mining pool, Bitcoin Energy Consumption, Exchange rate Inflation and oil price volatility, Portfolio spillovers, Negative/positive-induced news, Public opinion and increase in the value of cryptocurrencies generally and Bitcoin futures. Also, the digital currency market's inherent instability and unpredictability makes accurate projections impossible. Although some analysts predict that the price of Bitcoin will climb as time passes, others feel it will fall. Furthermore, prior to making any choices regarding investments, newbie traders and prospective investors ought to fully comprehend all of the elements that may impact the value of Bitcoin in future years.

Additional machine learning models and algorithms can be employed for bitcoin prediction in the future to get more insight and features such as understanding the next bitcoin halving season. The comparison made in this research between the forecasted and actual prices using the FPM and LSTM models revealed significant differences in their performance. The Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) for the LSTM model was found to be lower than that of FPM, while the Coefficient of Determination (R^2) of LSTM model achieved a significantly higher value compared to the Coefficient of Determination (R^2) of FPM model. These metrics serve as indicators of accuracy and precision for the models. In this scenario, LSTM outperformed the FPM with regards to accuracy and precision. The lower Mean

Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) values and the higher the Coefficient of Determination (R^2) value for the LSTM model compared to the values of the metrics for FPM suggest that LSTM provided more accurate predictions. This data shows the superior performance of the LSTM model compared to the FPM model.

5.2 Recommendation

To enhance future Bitcoin predictions, it is recommended to explore additional machine learning models and algorithms that can provide more insight and features. This could involve incorporating advanced techniques such as deep learning models or ensemble methods. Additionally, expanding the dataset used for prediction beyond the Investing.com, Ychart, or Yahoo Finance databases could help capture a wider range of factors influencing Bitcoin prices. It is crucial for beginner traders and investors to carefully analyze these factors and evaluate various prediction models before making any investment decisions. By gaining a comprehensive understanding of the crypto market's volatility characteristics, novice traders can mitigate risks and make informed investment choices.

REFERENCES

Abdulhakeem, S. A., and Hu, Q. (2021). Powered by Blockchain Technology, DeFi (Decentralized Finance) Strives to Increase Financial Inclusion of the Unbanked by Reshaping the World Financial System. Modern Economy, 12(01), 1–16. https://doi.org/10.4236/me.2021.121001

Ahram, T., Sargolzaei, A., Sargolzaei, S., Daniels, J., and Amaba, B. (2017). Blockchain technology innovations. 2017 IEEE Technology and Engineering Management Conference (TEMSCON). https://doi.org/10.1109/temscon.2017.7998367

Amsyar, I., Christopher, E., Dithi, A., Khan, A. N., and Maulana, S. (2020). The Challenge of Cryptocurrency in the Era of the Digital Revolution: A Review of Systematic Literature. Aptisi Transactions on Technopreneurship (ATT), 2(2), 153–159. https://doi.org/10.34306/att.v2i2.96

Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., McCallum, P., and Peacock, A. (2019). Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renewable and Sustainable Energy Reviews, 100(1), 143–174. https://doi.org/10.1016/j.rser.2018.10.014

Austin, J. (2021). Stock markets play “whack a mole” with Pump and Dump schemes. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3972431

Badea, L., and Mungiu-Pupazan, M. C. (2021). The Economic and Environmental Impact of Bitcoin. IEEE Access, 9, 48091–48104. https://doi.org/10.1109/access.2021.3068636

Barton, K. (2005). The implications of the Proceeds of Crime Act 2002 for banks and professionals. Journal of Banking Regulation, 6(2), 183–193. https://doi.org/10.1057/palgrave.jbr.2340191

Bellavitis, C., Fisch, C., and Wiklund, J. (2021). A comprehensive review of the global development of initial coin offerings (ICOs) and their regulation. Journal of

Business Venturing Insights, 15, e00213. https://doi.org/10.1016/j.jbvi.2020.e00213

Berentsen, A., and Schar, F. (2018). A Short Introduction to the World of Cryptocurrencies. Review, 100(1), 1–19. https://doi.org/10.20955/r.2018.1-16

Bhatnagar, M., Taneja, S., and Rupeika-Apoga, R. (2023). Demystifying the Effect of the News (Shocks) on Crypto Market Volatility. Journal of Risk and Financial Management, 16(2), 136. https://doi.org/10.3390/jrfm16020136

Borges, D., and Nascimento, M. C. V. (2022). COVID-19 ICU demand forecasting: A two-stage Prophet-LSTM approach. Applied Soft Computing, 125, 109181. https://doi.org/10.1016/j.asoc.2022.109181

Bouri, E., Das, M., Gupta, R., and Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. Applied Economics, 50(55), 5935–5949. https://doi.org/10.1080/00036846.2018.1488075

Bratspies, R. (2018). Cryptocurrency and the Myth of the Trustless Transaction. Michigan Telecommunications and Technology Law Review, 25(1), 1–58. https://repository.law.umich.edu/mttlr/vol25/iss1/2

Briola, A., Vidal-Tomás, D., Wang, Y., and Aste, T. (2022). Anatomy of a Stablecoin's failure: The Terra-Luna case. Finance Research Letters, 103358. https://doi.org/10.1016/j.frl.2022.103358

Bunjaku, F., Gjorgieva-Trajkovska2, O., and Miteva-Kacarski, E. (2017). CRYPTOCURRENCIES – ADVANTAGES AND DISADVANTAGES. Journal of Economics, 2(1), 31–39. https://js.ugd.edu.mk/index.php/JE/article/view/1933

Bunjaku, F., Gjorgieva-Trajkovska2, O., and Miteva-Kacarski, E. (2017). CRYPTOCURRENCIES – ADVANTAGES AND DISADVANTAGES. Journal of Economics, 2(1), 31–39. https://js.ugd.edu.mk/index.php/JE/article/view/1933

Chen, G., Xu, B., Lu, M. et al. (2018). Exploring blockchain technology and its potential applications for education. Smart Learn. Environ. 5, 1 . https://doi.org/10.1186/s40561-017-0050-x

Chen, X., Miraz, M. H., Gazi, Md. A. I., Rahaman, Md. A., Habib, Md. M., and Hossain, A. I. (2022). Factors affecting cryptocurrency adoption in digital business transactions:
The mediating role of customer satisfaction. Technology in Society, 70, 102059. https://doi.org/10.1016/j.techsoc.2022.102059

Chen, Y. (2018). Blockchain tokens and the potential democratization of entrepreneurship and innovation. Business Horizons, 61(4), 567–575. https://doi.org/10.1016/j.bushor.2018.03.006

Chohan, U. W. (2017). A History of Bitcoin. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.304787

Chohan, U. W. (2021). Oversight and Regulation of Cryptocurrencies: BitLicense. Cryptofinance, 105–120. https://doi.org/10.1142/9789811239670_0006

Coskuner, G., Jassim, M. S., Zontul, M., and Karateke, S. (2020). Application of artificial intelligence neural network modeling to predict the generation of domestic, commercial and construction wastes. Waste Management and Research, 0734242X2093518. https://doi.org/10.1177/0734242x20935181

Cousins, K., Subramanian, H., and Esmaeilzadeh, P. (2019). A Value-sensitive Design Perspective of Cryptocurrencies: A Research Agenda. Communications of the Association for Information Systems, 511–547. https://doi.org/10.17705/1cais.04527

Deniz, E. A., and Teker, D. (2020). Crypto currency applications in financial markets: factors affecting crypto currency prices. Pressacademia, 11(1), 34–37. https://doi.org/10.17261/pressacademia.2020.1235

DeVon, cheyenne. (2022). Bitcoin lost over 60% of its value in 2022—here's how much 6 other popular cryptocurrencies lost. CNBC. https://www.cnbc.com/2022/12/23/bitcoinlost-over-60-percent-of-its-value-in-2022.html

Dolar, B., and Shughart, W. F. (2012). The USA Patriot Act's differential impact on large and small banks: Evidence from California's high-risk money laundering and related financial crime areas. Journal of Banking Regulation, 13(2), 127–146. https://doi.org/10.1057/jbr.2011.22

Eenmaa-Dimitrieva, H., and Schmidt-Kessen, M. J. (2019). Creating markets in no-trust environments: The law and economics of smart contracts. Computer Law and Security Review, 35(1), 69–88. https://doi.org/10.1016/j.clsr.2018.09.003

Efanov, D., and Roschin, P. (2018). The All-Pervasiveness of the Blockchain Technology. Procedia Computer Science, 123, 116–121. https://doi.org/10.1016/j.procs.2018.01.019

Engle, R. (2004). Risk and Volatility: Econometric Models and Financial Practice. American Economic Review, 94(3), 405–420. https://doi.org/10.1257/0002828041464597

F.A. Enoksen, Ch.J. Landsnes, K. Lučivjanská, P. Molnár (2020). Understanding risk of bubbles in cryptocurrencies. (2020). Journal of Economic Behavior and Organization, 176, 129–144. https://doi.org/10.1016/j.jebo.2020.05.005

Fanusie, Y. J., Kahler, M., Forstater, M., Findley, M. G., Vittori, J., and Westenberg, E. (2018). Financial Authorities Confront Two Cryptocurrency Ecosystems. JSTOR. https://www.jstor.org/stable/resrep21429.8

Farell, R. (2015). An Analysis of the Cryptocurrency Industry. Www.semanticscholar.org. https://www.semanticscholar.org/paper/An-Analysis-of-the-Cryptocurrency-Industry-Farell/a68100519819845d990d496e9d8827de1394825b

Fu, S., Wang, Q., Yu, J., and Chen, S. (2022). FTX Collapse: A Ponzi Story. ArXiv: 2212.09436 [Cs]. https://arxiv.org/abs/2212.09436

GÜLERYÜZ, D., and ÖZDEN, E. (2020). LSTM ve Facebook Prophet Kullanarak Brent Ham Petrol Trendinin Tahmini. European Journal of Science and Technology. https://doi.org/10.31590/ejosat.759302

Hassan, Salman and Azhar, Tehseen. (2022). CURRENT CHALLENGES OF CRYPTOCURRENCIES FACED BY GOVERNMENTS. 5. 1484-1497.

Henriques, I., and Sadorsky, P. (2018). Can Bitcoin Replace Gold in an Investment Portfolio? Journal of Risk and Financial Management, 11(3), 48. https://doi.org/10.3390/jrfm11030048

Herrera-Joancomartí, J. (2015). Research and Challenges on Bitcoin Anonymity. Data Privacy Management, Autonomous Spontaneous Security, and Security Assurance, 3–16. https://doi.org/10.1007/978-3-319-17016-9_1

Isidore, C. (2021, April 28). Tesla bought $1.5 billion in bitcoin early this year. By the end of March, it was worth $2.5 billion | CNN Business. CNN. https://edition.cnn.com/2021/04/28/investing/tesla-bitcoin/index.html#:~:text=The%20company%20disclosed%20in%20February

Jacquez, T. (2016). Cryptocurrency the new money laundering problem for banking, law enforcement, and the legal system (Doctoral dissertation, Utica College). https://www.proquest.com/openview/daa0d91607166b4d9e3a0accbca6cc09/1/index

Kamps, J., and Kleinberg, B. (2018). To the moon: defining and detecting cryptocurrency pump-and-dumps. Crime Science, 7(1). https://doi.org/10.1186/s40163-018-0093-5

Karateke, S., Zontul, M., Bozkurt, N. E., and Aslan, Z. (2021). Wavelet-ANFIS hybrid model for MODIS NDVI prediction. Journal of Applied Remote Sensing, 15(02). https://doi.org/10.1117/1.jrs.15.024519

Kethineni, S., and Cao, Y. (2019). The Rise in Popularity of Cryptocurrency and Associated Criminal Activity. International Criminal Justice Review, 30(3). https://doi.org/10.1177/1057567719827051

Khan, R., and Hakami, T. A. (2021). Cryptocurrency: usability perspective versus volatility threat. Journal of Money and Business, ahead-of-print(ahead-of-print). emerald. https://doi.org/10.1108/jmb-11-2021-0051

Kim, C. Y., and Lee, K. (2018, January 1). Risk Management to Cryptocurrency Exchange and Investors Guidelines to Prevent Potential Threats. IEEE Xplore. https://doi.org/10.1109/PlatCon.2018.8472760

Lawnik, M., and Banasik, A. (2020). Delphi Method Supported by Forecasting Software. Information, 11(2), 65. https://doi.org/10.3390/info11020065

Lu, C. (2022). Cryptocurrency and Digital Assets: A Positive Tool for Economic Growth in Developing Countries. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4177415

M. D. Haris, D. Adytia, and A. W. Ramadhan, “Air temperature forecasting with long short-term memory and prophet: a case study of jakarta, indonesia,” in 2022 International Conference on Data Science and Its Applications (ICoDSA) (IEEE, 2022) pp. 251–256.

Mahdi, E., Leiva, V., Mara’Beh, S., and Martin-Barreiro, C. (2021). A New Approach to Predicting Cryptocurrency Returns Based on the Gold Prices with Support Vector Machines during the COVID-19 Pandemic Using Sensor-Related Data. Sensors, 21(18), 6319. https://doi.org/10.3390/s21186319

Marella, V., Upreti, B., Merikivi, J., and Tuunainen, V. K. (2020). Understanding the creation of trust in cryptocurrencies: the case of Bitcoin. Electronic Markets. https://doi.org/10.1007/s12525-019-00392-5

Mazikana, A. T. (2018). The Impact of Cryptocurrencies in Zimbabwe. An Analysis of Bitcoins. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3376307

Mironeanu, A., Irimia, B., Săndulescu, V., and Teodoroiu, C. (2021). The impact of Tesla’s bitcoin investment and its plans to accept it as payment method on the evolution of bitcoin. Proceedings of the International Conference on Business Excellence, 15(1), 58–74. https://doi.org/10.2478/picbe-2021-0007

Mukhopadhyay, U., Skjellum, A., Hambolu, O., Oakley, J., Yu, L., and Brooks, R. (2016, December 1). *A brief survey of Cryptocurrency systems*. IEEE Xplore. https://doi.org/10.1109/PST.2016.7906988

Murray, A., Kim, D., and Combs, J. (2022). The promise of a decentralized Internet: What is web 3.0 and HOW can firms prepare? Business Horizons. https://doi.org/10.1016/j.bushor.2022.06.002

Niranjanamurthy, M., Nithya, B. N., and Jagannatha, S. (2018). Analysis of Blockchain technology: pros, cons and SWOT. Cluster Computing, 22. https://doi.org/10.1007/s10586-018-2387-5

Omarova, S. T. (2020, April 15). Dealing With Disruption: Emerging Approaches to FinTech Regulation. Papers.ssrn.com. https://ssrn.com/abstract=3576609

Ouma, Y. O., Cheruyot, R., and Wachera, A. N. (2021). Rainfall and runoff time-series trend analysis using LSTM recurrent neural network and wavelet neural network with satellite-based meteorological data: case study of Nzoia hydrologic basin. Complex and Intelligent Systems. https://doi.org/10.1007/s40747-021-00365-2

Patandung, S., and Jatnika, I. (2021). The FB Prophet Model Application to the Growth Prediction of International Tourists in Indonesia during the COVID-19 Pandemic. International Research Journal of Advanced Engineering and Science, 6(2), 110-115.

Pavlidis, G. (2020). Financial information in the context of anti-money laundering. Journal of Money Laundering Control, ahead-of-print(ahead-of-print). https://doi.org/10.1108/jmlc-10-2019-0081

Peters, G. W., and Panayi, E. (2016). Understanding Modern Banking Ledgers Through Blockchain Technologies: Future of Transaction Processing and Smart Contracts on the Internet of Money. In Banking Beyond Banks and Money (pp. 239–278). https://doi.org/10.1007/978-3-319-42448-4_13

Pilkington, M. (2016). Blockchain technology: principles and applications. Research Handbook on Digital Transformations, 225–253. https://doi.org/10.4337/9781784717766.00019

Platt, M., Ojeka, S., Andreea Elena Drăgnoiu, Oserere Ibelegbu, Pierangeli, F., and Johannes Sedlmeir. (2022). How to Make Users Adopt More Sustainable Cryptocurrencies: Evidence from Nigeria. ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2208.00280

Rajasekaran, A. S., Azees, M., and Al-Turjman, F. (2022). A comprehensive survey on blockchain technology. Sustainable Energy Technologies and Assessments, 52, 102039. https://doi.org/10.1016/j.seta.2022.102039

Ramos, S., Pianese, F., Leach, T., and Oliveras, E. (2021). A great disturbance in the crypto: Understanding cryptocurrency returns under attacks. Blockchain: Research and Applications, 100021. https://doi.org/10.1016/j.bcra.2021.100021

Riley, J. (2021). The Current Status of Cryptocurrency Regulation in China and Its Effect around the World. China and WTO Review, 7(1), 135–152. https://doi.org/10.14330/cwr.2021.7.1.06

Rosales, A. (2019). Radical rentierism: gold mining, cryptocurrency and commodity collateralization in Venezuela. Review of International Political Economy, 26(6), 1311–1332. https://doi.org/10.1080/09692290.2019.1625422

Shi, S., and Shi, Y. (2019). Bitcoin futures: trade it or ban it? The European Journal of Finance, 27(4-5), 381–396. https://doi.org/10.1080/1351847x.2019.1647865

Signer, C. (2018). ETH Library Gas Cost Analysis for Ethereum Smart Contracts. https://doi.org/10.3929/ethz-b-000312914

Singh, B., and Kant, S. (2019). Crypto Currencies/Blockchain and the Banking System. The Journal of Indian Institute of Banking and Finance. https://www.researchgate.net/publication/339149786_Crypto_CurrenciesBlockchain_and_the_Banking_System

Sotiropoulou, A., and Guégan, D. (2017). Bitcoin and the challenges for financial regulation. Capital Markets Law Journal, 12(4), 466–479. https://doi.org/10.1093/cmlj/kmx037

Starovoitov, V. V., and Golub, Yu. I. (2021). Data normalization in machine learning. Informatics, 18(3), 83–96. https://doi.org/10.37661/1816-0301-2021-18-3-83-96

Sukarno, K. S., and Pujiyono. (2020). The Use of Cryptocurrency as a Payment Instrument. Proceedings of the 3rd International Conference on Law and Governance (ICLAVE 2019). https://doi.org/10.2991/aebmr.k.200321.048

Suzuki, Y., and Oue, R. (2016). FinTech legislation in Japan. Global Banking and Financial Policy Review.

T. Toharudin, R. S. Pontoh, R. E. Caraka, S. Zahroh, Y. Lee, and R. C. Chen, “Employing long short-term memory and facebook prophet model in air temperature forecasting,” Communications in Statistics-Simulation and Computation , 1–24 (2020).

Taskinsoy, J. (2021, October 13). Bitcoin: A New Digital Gold Standard in the 21st Century? Papers.ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3941857

Teichmann, F. M. J., and Falker, M.-C. (2020). Cryptocurrencies and financial crime: solutions from Liechtenstein. Journal of Money Laundering Control, ahead-of-print(ahead-of-print). https://doi.org/10.1108/jmlc-05-2020-0060

Tijan, E., Aksentijević, S., Ivanić, K., and Jardas, M. (2019). Blockchain Technology Implementation in Logistics. Sustainability, 11(4), 1185. https://doi.org/10.3390/su11041185

Todorov, T. (2017). Bitcoin – an innovative payment method with a new type of independent currency. Trakia Journal of Science, 15(Suppl.1), 163–166. https://doi.org/10.15547/tjs.2017.s.01.029

Triebe, O., Hewamalage, H., Pilyugina, P., Laptev, N., Bergmeir, C., and Rajagopal, R. (2021). NeuralProphet: Explainable Forecasting at Scale. ArXiv:2111.15397 [Cs, Stat]. https://arxiv.org/abs/2111.15397

Tüzen, F., Erbaş, S., and Olmuş, H. (2018). A simulation study for count data models under varying degrees of outliers and zeros. Communications in Statistics - Simulation and Computation, 49(4), 1078–1088. https://doi.org/10.1080/03610918.2018.1498886

Wang, Y., Xu, C., Li, Y., Wu, W., Gui, L., Ren, J., and Yao, S. (2020). An Advanced Data-Driven Hybrid Model of SARIMA-NNNAR for Tuberculosis Incidence Time Series Forecasting in Qinghai Province, China. Infection and Drug Resistance, Volume 13, 867–880. https://doi.org/10.2147/idr.s232854

Wilson, C. (2019). Cryptocurrencies: The Future of Finance? Contemporary Issues in International Political Economy, 359–394. https://doi.org/10.1007/978-981-13-6462-4_16

Wohrer, M., and Zdun, U. (2018). Smart contracts: security patterns in the ethereum ecosystem and solidity. 2018 International Workshop on Blockchain Oriented Software Engineering (IWBOSE). https://doi.org/10.1109/iwbose.2018.8327565

Wronka, C. (2021). Financial crime in the decentralized finance ecosystem: new challenges for compliance. Journal of Financial Crime, ahead-of-print(ahead-of-print). https://doi.org/10.1108/jfc-09-2021-0218

Xi, D., O'Brien, T. I., and Irannezhad, E. (2020). Investigating the Investment Behaviors in Cryptocurrency. The Journal of Alternative Investments, jai.2020.1.105. https://doi.org/10.3905/jai.2020.1.108

Yaga, D., Mell, P., Roby, N., and Scarfone, K. (2018). Blockchain Technology Overview. National Institute of Standards and Technology. https://doi.org/10.6028/nist.ir.8202

Yao, Y., Angelov, I., and Rasmus-Vorrath, J. K. (2019). Blockchain Security and Demonstration. Www.academia.edu. Retrieved March 14, 2023, from https://www.academia.edu/35349686/Blockchain_Security_and_Demonstration

Yin, L., Nie, J., and Han, L. (2021). Understanding cryptocurrency volatility: The role of oil market shocks. International Review of Economics and Finance, 72, 233–253. https://doi.org/10.1016/j.iref.2020.11.013

Yli-Huumo, J., Ko, D., Choi, S., Park, S., and Smolander, K. (2016). Where Is Current Research on Blockchain Technology?—A Systematic Review. PLOS ONE, 11(10), e0163477. https://doi.org/10.1371/journal.pone.0163477

Zhang, R., Xue, R., and Liu, L. (2019). Security and Privacy on Blockchain. ACM Computing Surveys, 52(3), 1–34. https://doi.org/10.1145/3316481

Zhang, R., Xue, R., and Liu, L. (2019). Security and Privacy on Blockchain. ACM Computing Surveys, 52(3), 1–34. https://doi.org/10.1145/3316481

Zheng, Z., Xie, S., Dai, H.-N., Chen, W., Chen, X., Weng, J., and Imran, M. (2020). An overview on smart contracts: Challenges, advances and platforms. Future Generation Computer Systems, 105, 475–491. https://doi.org/10.1016/j.future.2019.12.019

APPENDIXES

APPENDIX 1: SIMILARITY REPORT

Thanko

ORIGINALITY REPORT

8%	6%	4%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.researchgate.net Internet Source	1%
2	mdpi-res.com Internet Source	<1%
3	Submitted to Liverpool John Moores University Student Paper	<1%
4	Afees A. Salisu, Ahamuefula E. Ogbonna. "The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect", Global Finance Journal, 2021 Publication	<1%
5	ebin.pub Internet Source	<1%
6	Submitted to School of Oriental & African Studies Student Paper	<1%
7	link.springer.com Internet Source	<1%

www.mdpi.com

8	Internet Source	<1%
9	Submitted to University of Northumbria at Newcastle Student Paper	<1%
10	Wenjun Feng, Zhengjun Zhang. "Currency exchange rate predictability: the new power of Bitcoin prices", Journal of International Money and Finance, 2023 Publication	<1%
11	"Advanced Analytics and Learning on Temporal Data", Springer Science and Business Media LLC, 2023 Publication	<1%
12	Submitted to CSU, San Diego State University Student Paper	<1%
13	www.fsa.go.jp Internet Source	<1%
14	Submitted to University of Bradford Student Paper	<1%
15	Submitted to University of Leicester Student Paper	<1%
16	folk.ntnu.no Internet Source	<1%
17	www.grafiati.com Internet Source	<1%

18	www.ncsl.org Internet Source	<1 %
19	Submitted to University of Wollongong Student Paper	<1 %
20	Submitted to University of KwaZulu-Natal Student Paper	<1 %
21	www.ademcetinkaya.com Internet Source	<1 %
22	Wenjuan Xiong, Rachel E. Stirling, Daniel E. Payne, Ewan S. Nurse et al. "Forecasting seizure likelihood from cycles of self-reported events and heart rate: a prospective pilot study", eBioMedicine, 2023 Publication	<1 %
23	fst.univ-biskra.dz Internet Source	<1 %
24	journals.sagepub.com Internet Source	<1 %
25	assets-prod.mckinsey.com Internet Source	<1 %
26	eiti.org Internet Source	<1 %
27	forecasting-encyclopedia.com Internet Source	<1 %

28	Akanksha Jalan, Roman Matkovskyy, Andrew Urquhart. "What effect did the introduction of Bitcoin futures have on the Bitcoin spot market?", The European Journal of Finance, 2021 Publication	<1 %
29	core.ac.uk Internet Source	<1 %
30	doaj.org Internet Source	<1 %
31	essay.utwente.nl Internet Source	<1 %
32	Submitted to usep Student Paper	<1 %
33	www.biorxiv.org Internet Source	<1 %
34	www.icaew.com Internet Source	<1 %
35	www.matec-conferences.org Internet Source	<1 %
36	www.newsbtc.com Internet Source	<1 %
37	www.um.edu.mt Internet Source	<1 %

38	Ajithakumari Vijayappan Nair Biju, Ann Susan Thomas. "Uncertainties and ambivalence in the crypto market: an urgent need for a regional crypto regulation", SN Business & Economics, 2023 Publication	<1 %
39	Ao Shu, Feiyang Cheng, Jianlei Han, Zini Liang, Zheyao Pan. "Arbitrage across different Bitcoin exchange venues: Perspectives from investor base and market related events", Accounting & Finance, 2023 Publication	<1 %
40	Submitted to CSU, San Jose State University Student Paper	<1 %
41	Sumudu Senanayake, Biswajeet Pradhan, Abdullah Alamri, Hyuck-Jin Park. "A new application of deep neural network (LSTM) and RUSLE models in soil erosion prediction", Science of The Total Environment, 2022 Publication	<1 %
42	b3b7dd1a-d8cb-4579-8cfc-f21897e0f1ee.filesusr.com Internet Source	<1 %
43	cle.kku.ac.th Internet Source	<1 %
44	irep.iium.edu.my Internet Source	<1 %

45	journals.plos.org Internet Source	<1 %
46	mpra.ub.uni-muenchen.de Internet Source	<1 %
47	repositori.upf.edu Internet Source	<1 %
48	tojqih.net Internet Source	<1 %
49	www.cek.ef.uni-lj.si Internet Source	<1 %
50	"Computational Methods and Data Engineering", Springer Science and Business Media LLC, 2021 Publication	<1 %
51	0-www-mdpi-com.brum.beds.ac.uk Internet Source	<1 %
52	Submitted to City University Student Paper	<1 %
53	Hui Hu, Shuaizhou Xiong, Yi Chen, Lin Ye, Shuliang Zhao, Kun Qian, Michael De Domenici. "Prediction of Post-COVID-19 Economic and Environmental Policy and Recovery Based on Recurrent Neural Network and Long Short-Term Memory Network", Environmental Research Communications, 2022	<1 %

Publication

54	Kochar Sahibpreet Singh. "chapter 9 Cryptocurrency Adoption", IGI Global, 2023 Publication	<1 %
55	Stephen Chan, Jeffrey Chu, Yuanyuan Zhang, Saralees Nadarajah. "An extreme value analysis of the tail relationships between returns and volumes for high frequency cryptocurrencies", Research in International Business and Finance, 2021 Publication	<1 %
56	centaur.reading.ac.uk Internet Source	<1 %
57	cocodoc.com Internet Source	<1 %
58	dc.uwm.edu Internet Source	<1 %
59	heim.ifi.uio.no Internet Source	<1 %
60	policyreview.info Internet Source	<1 %
61	research-api.cbs.dk Internet Source	<1 %
62	s3-ap-southeast-1.amazonaws.com Internet Source	<1 %

63	service-finder.eu Internet Source	<1 %
64	submit.confbay.com Internet Source	<1 %
65	tru.uni-sz.bg Internet Source	<1 %
66	www.cbr.ru Internet Source	<1 %
67	www.engineeringletters.com Internet Source	<1 %
68	www.europeanproceedings.com Internet Source	<1 %
69	www.ndl.ethernet.edu.et Internet Source	<1 %
70	Zhijian Qu, Jian Li, Xinxing Hou, Jianglin Gui. "A D-stacking dual-fusion, spatio-temporal graph deep neural network based on a multi-integrated overlay for short-term wind-farm cluster power multi-step prediction", Energy, 2023 Publication	<1 %
71	Jihed Ben Nouir, Hayet Ben Haj Hamida. "How do Economic policy uncertainty and geopolitical risk drive Bitcoin volatility?",	<1 %

Research in International Business and Finance, 2022
Publication

72	digitalcommons.wayne.edu Internet Source	<1 %
73	doi.org Internet Source	<1 %

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	On		