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DATA SCIENCE IN FINANCIAL MARKETS PROJECT REPORT

on

Network and Hurst Exponent Based Portfolio Optimization of Cryptocurrencies

Submitted by:

Sai Sri Mohnit Akula (220575) Uday Sushanth Malleboina (220588) Sai Ram Aditya Kasarla (220568)

under mentorship of

Dr. Hirdesh Kumar Pharasi (Assistant Professor)



Department of Computer Science Engineering School of Engineering and Technology

BML MUNJAL UNIVERSITY, GURUGRAM (INDIA)

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CANDIDATES DECLARATION

Therefore, we affirm that the project work is our independent work carried out

during a period from August 2024 to December 2024 titled as "Network and Hurst

Exponent Based Portfolio Optimization of Cryptocurrencies" submitting in partial

fulfillment of the requirements for the Degree of Bachelor of Technology in School

of Engineering and Technology, BML Munjal University with University Roll No.

220575, 220588, 220568 under the guidance andi.

(Sai Sri Mohnit Akula)

(Uday Sushanth Malleboina)

(Sai Ram Aditya Kasarla)

SUPERVISOR'S DECLARATION

The candidate has filled the above statement to the best of our knowledge and

hereby we are certifying the above said statement.

Faculty Supervisor Name: Dr. Hirdesh Kumar Pharasi

Signature:

2

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I am highly thankful to **Dr. Hirdesh Kumar Pharasi**, Assistant Professor, BML Munjal University, Gurugram, for giving the supervision from August – December 2024 to conduct seminar/case study.

A sincere appreciative gratitude is offered here to **Dr. Hirdesh Kumar Pharasi** for extending excellent assistance in doing my work. .fail to do it in such a manner because there wasn't any wise counsel and able guidance when accomplishing the training.

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LIST OF FIGURES

Figure	Figure Description		
No.		No.	
1	Histograms of different log returns of	13	
	Cryptocurrencies		
2	Hurst Exponents in Pre-Covid period	16	
3	Correlation between Cryptocurrencies	16	
	Pre-Covid		
4	Dendrogram for pre-Covid era	17	
5	Minimum Spanning Tree for correlation in pre-Covid era	17	
6	Hurst Exponents in Post-Covid period	18	
7	Correlation between Cryptocurrencies Post-Covid	18	
8	Dendrogram for post-Covid era	19	
9	Minimum Spanning Tree for correlation in post-Covid era	19	

TABLE OF CONTENTS

Sr.	Contents	Page No.
No.		
1.	Abstract	6
2.	Introduction	7-9
3.	Literature Review	10-12
4.	Methodology	13-16
5.	Analysis and Discussion of Results	17-21
6.	Conclusion and Future Scope	22
7.	References	23

ABSTRACT

This project integrates network analysis and Hurst exponent in cryptocurrency portfolio optimisation. In our case, network analysis in the evaluation process reveals the connection and grouping of cryptocurrencies; while the Hurst exponent is useful in measuring the probable random long-term pattern and persistence of the market. Combining these methods, our goal is to create a new approach to the selection and portfolio management in the most turbulent market that is the cryptocurrency one. As it can be noted from the results discussed above, additional sophisticated mathematical methods can help to achieve better investment solutions and minimize risks.

1. INTRODUCTION

Digital financial asset known as cryptocurrencies alter the financial system all over the world through decentralization, transparency, and new means of trading. However, strengths are often associated with more variability and interact with each other in a way that makes portfolio analysis and risk evaluation very challenging. Most conventional approaches of portfolio optimization do not adequately model this market. Of these, this project centers on the application of two striking methods; that is, network analysis and the Hurst exponent.

Network analysis examines the connectivity and dependency of cryptocurrencies and the self-similarity exponent of dynamics. Together, they will form a flexible foundation that can serve as a framework to find the best configurations of cryptocurrency portfolios; As the market for cryptocurrencies progresses at a fast pace, this is crucial for investors.

1.1 Problem Statement

In cryptocurrency market, investors face certain limitations because their dynamics are high, and the relationships between the cryptocurrencies are changeable; moreover, the prices are rather volatile. Fundamental approaches used in portfolio optimization do not allow to properly reflect certain specifics of this market like the coupling of different cryptocurrencies and temporal properties of price patterns — whether they are persistent or stochastic. Experts agree that investors require new ways of identifying trends and examining their activities in order to calculate risks and maximize gains...

1.2 Objectives

- Understand Interrelationships: Use network methodology in order to reveal groups and ties and determine relationships as well as tendencies between involving cryptocurrencies.
- **Measure Trend Persistence:** Use Hurst exponent to measure market memory and predictability, enable to find the assets with regular performance direction.
- **Develop Portfolio Strategies:** Create a dictionary of portfolio optimization that combines the ideas from the network analysis and calculations of Hurst exponent.
- Mitigate Investment Risks: Overcome the fluctuations in the market through advanced analytics that intensifies the risk management approach.
- Facilitate Real-World Implementation: Investment decision support services that help investors generate optimal results within investing in the cryptocurrency market.

1.3 Motivation

The new market that is cryptocurrencies has done a lot to expand within the previous decade and is offering amazing and unique opportunities for an investment along with the possible risks. Unlike other financial instruments, Cryptocurrencies present a high level of fluctuation as a result risk management is of major importance. This forced us to consider creative solutions due to the volatile nature of this market and the tremendous rates at which it developed. Using the standard classical portfolio optimization techniques is not likely to be adequate for such an environment. It is toward filling this gap that this project aims to use techniques such as network analysis and the Hurst exponent. These tools help to get deeper information about the market behavior, which allows to create perfect strategies that consider main tendencies of cryptocurrency investments.

1.4 Significance

This project is important since it serves to fill a gap within the cryptocurrency portfolio management. Conventional optimization models fail when facing challenges of cryptocurrencies, volatility and high frequency of price changes for instance. By applying the network analysis we get additional insights about the connections and clusters in the crypto market which will make diversification more effective. Trend persistence and market memory are important values added because the Hurst exponent speaks of predictability. Altogether, such tools create the premise for better portfolio management, minimising threats and enhancing the rates. This work has clear context and relevance for practicing self-investors as well as practising financial analysts aiming to understand the specifics of cryptocurrency markets' dynamics.

1.5 Challenges

- **Data Collection and Quality:** Cryptocurrency markets are around the clock and offer tremendous amounts of data. The biggest difficulty was being unable to get good amount of data as most of the websites are paid to maintain the quality, reliability and completeness of this data.
- Market Volatility: Compared to tangible assets, fluctuation of price of cryptocurrencies remains volatile and unpredictable, which increases the problem of modeling and optimization..
- Complex Interdisciplinary Approach: Applying the concept of network theory, fractal analysis, and financial modeling integration is only possible with the knowledge of all three fields.
- Scalability and Adaptability: The first challenge is to assure that the
 optimization framework continues to be efficient and scalable under
 different markets while being applicable to a varying range and types of
 cryptocurrencies.

2. LITERATURE REVIEW

2.1 Summary of Research Works

1. "The cryptocurrency market: A network analysis" - (2018)

The proposed problem settings focus on analyzing dependencies and linkages within the cryptocurrency market using methods of network analysis. It aims at trying to construct a Minimum Spanning Tree (MST) and a dendrogram based on the return properties of the cryptocurrencies using Pearson correlation matrix. With the help of the 16 most actively traded cryptocurrencies between July 23, 2017, and February 16, 2018, this paper will reveal dependencies and hierarchy in the relationship of those assets.

2. "Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis" -(2021)

This paper analyses the effects of the COVID-19 pandemic on the cryptocurrency market with the network analysis of 69 mature coins from August 2019 to August 2020. It detects a large degree of market integration during the financial panic in March 2020 but attributes a return to pre-panic integration levels. These techniques are dynamic correlation networks, degree centrality and betweenness centrality to monitor market shifts and nodes. These include indications that short-term unsustainability increases, herding behavior intensifies, and diversification possibilities shrink in the course of market shocks.

3. "Cryptocurrencies and Long-Range Trends" -(2023)

In this paper, we investigate the long-range dependencies, and the dynamic behavior of the markets from 37 cryptocurrencies by applying the Hurst exponent. It focuses on the specificity and uncertainty of the cryptocurrency markets as compared with the financial systems. It assesses market efficiency and memory effects through several time scales using DFA & R/S analysis. The result of the analysis shows that the cryptocurrencies exhibit different characteristics of persistence, randomness as well as mean reversion. The results may be very helpful for academics and investors to understand the efficiency and the future prospective of the cryptocurrency markets.

2.2 Comparison Table

Paper Link	Author(s)	Model Used	Conclusion Drawn
Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis	David Vidal-Tomás	Network Analysis,Network Topology,Multiple Spanning Tree	In this work, a network approach is used to study cryptocurrency markets in the context of COVID-19, with the degree centralization and betweenness centralization coefficients that prove the interconnection and synchronization of markets or their shift. The results also indicate that the degree of connectedness has risen during the period of pandemic high, or increased herding or reduction in diversification.
The cryptocurrency market: A network analysis	Carlos Jaureguizar Francés Pilar Grau-Carles Diego Jaureguizar Arellano	Minimum Spanning Tree , Pearson Correlation	The provided problem statement explores the dependencies and relationships within the cryptocurrency market using advanced network analysis techniques.
Cryptocurrencies and Long-Range Trends	Monica Alexiadou, Emmanouil Sofianos, Periklis Gogas and Theophilos Papadimitriou	R/S , DFA for Hurst exponent	In this research, they use the Hurst exponent to detect long range properties, which are uncommon in the analysis of this type of market. Also, as noted earlier, the application of the R/S analysis and the DFA analysis Detecting astronomic

3. DATASET ANALYSIS

3.1 Dataset Collection

3.1.1 Sources:

The cryptocurrency data was sourced using the Yahoo Finance API (yfinance), focusing on six cryptocurrencies: Those include BTC, ETH, XRP, LTC, BCH, and ADA. The data range is defined from the beginning of the year January 1st, 2020 to the end of year December 31st, 2021 and preponderantly, daily closing prices are utilized in this research.

3.1.2 Data Types:

This dataset contains time series data high, and close prices etc of Cryptocurrencies with numeric measurements. Other changes such as the logarithmic returns are then calculated for the purpose of analyzing trends and cycles.

3.2 Data Preprocessing

3.2.1 Handling Missing Values:

Missing values in cryptocurrency data were addressed using linear interpolation, ensuring data continuity without losing trends.

3.2.2 Normalization:

Logarithmic transformations were used to compute the returns and then the scale of comparison for different cryptocurrencies was brought to the same level.

3.3 Exploratory Data Analysis

Some of the figures within EDA are showing time series of prices, histograms of log returns and various statistics. They just facilitate the understanding of price behavior and the distribution of returns.

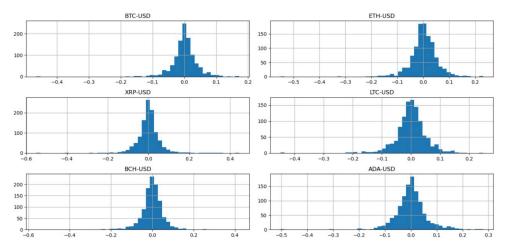


Figure 1: Histograms of different log returns of Cryptocurrencies

4. METHODOLOGY

4.1 Model Selection

The study uses a variety of techniques that best fit the analysis of cryptocurrency market dynamics before and after COVID-19. Network analysis and Hurst exponent are the two central methodologies used.

4.1.1 Why Network Analysis and Hurst Exponent?

Network Analysis

- It captures interconnections among cryptocurrencies based on their returns.
- It captures market structure, relationships, and critical entities influencing the network.
- MST provides a highly efficient way of reducing the complex market graph into an interpretable structure and thereby showing clusters and central nodes.

Hurst Exponent

Measures the efficiency and trend behavior of returns of cryptocurrencies. Determines if the market is mean reverting (H<0.5), follows a random walk (H~0.5), or is persistent (H>0.5). It will help contrast pre- and post-COVID market behavior.

4.1.2 Feature Engineering

• Price Data:

The daily closing prices of chosen cryptocurrencies are captured and used to compute log returns for capturing the true dynamics of percentage changes.

• Moving Averages:

- Incorporate temporal dependencies like previous days' prices and trends.
- Technical indicators such as moving averages (7-day, 30-day) are used for trend identification.

• Correlation-Based Features:

- Create a distance matrix from pairwise correlation to capture similarity between cryptocurrencies.
- Underpin cluster and MST formation.

4.1.3 Analysis and Visualization

• Hurst Exponent Analysis:

- The Hurst exponent is determined with the use of R/S analysis in determining the behavior in the market. Result are classified to be in three groups, namely,
- \circ Mean reverting (H < 0.45)
- Random walk $(0.45 \le H \le 0.60)$

- \circ Persistent/Trending ($H \ge 0.60$ \).
- It draws pre- and post-COVID comparative analyses to understand changes in the efficiency of the market.

Network Creation and MST:

- It develops an MST on the distance matrix.
- Degree centrality, closeness centrality, and centrality of the network for finding the most influential cryptocurrencies in the network.

• Clustering and Community Detection**

- Grouping dendrograms show the structural visualization of groupings of cryptocurrencies.
- Modular communities are discovered in the MST, where structural differences prior to and post-COVID are present.

4.2 Evaluation Metrics

4.2.1 Hurst exponent trends:

Statistical estimates are utilized to compute if there exists a change in efficiency in markets.

4.2.2 Network Metrics:

Measures for calculating centrality and modularity scores depict the interconnections and structures of the markets.

Analysis and Discussion of Results

- A comparative analysis of periods before COVID (2018–2019) with periods after
 COVID (2020–2022) shows changes in efficiency as well as connectivity.
- The impact of centralised cryptocurrencies and the robustness of clusters are discussed with external shocks such as COVID 19.

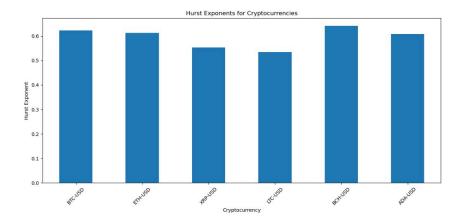


Figure 2: Hurst Exponents in Pre-Covid period

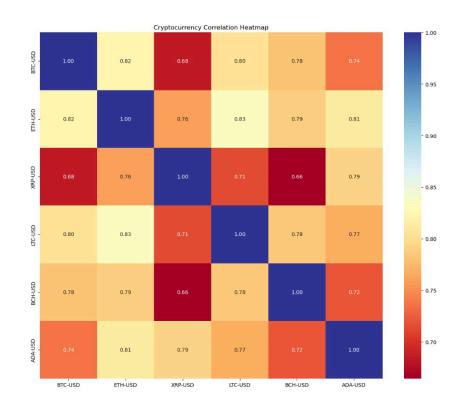


Figure 3: Correlation between Cryptocurrencies Pre-Covid

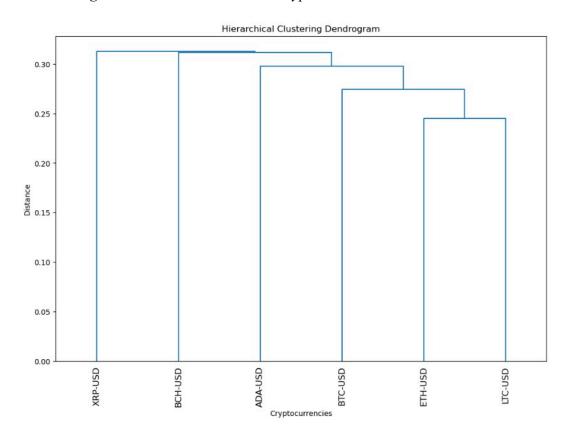


Figure 4: Dendrogram for pre-Covid era

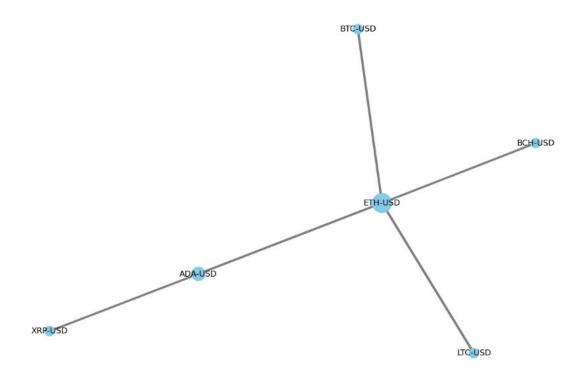


Figure 5: Minimum Spanning Tree for correlation in pre-Covid era

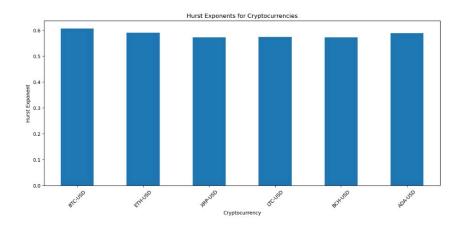


Figure 6: Hurst Exponents in Post-Covid period

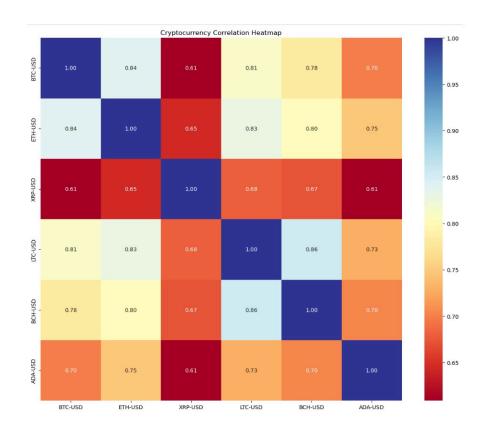


Figure 7: Correlation between Cryptocurrencies Post-Covid

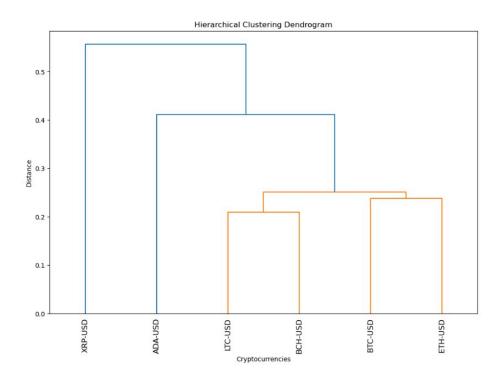


Figure 8: Dendrogram for post-Covid era

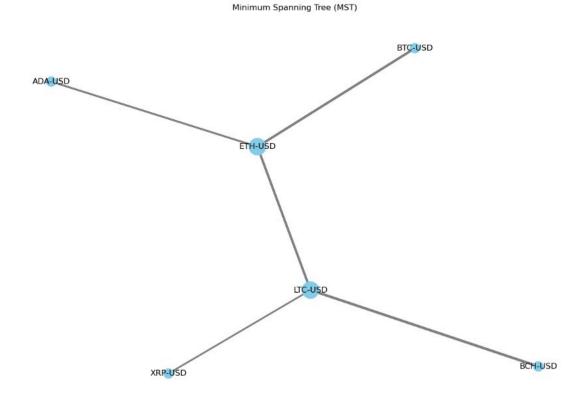


Figure 9: Minimum Spanning Tree for correlation in post-Covid era

CONCLUSION AND FUTURE SCOPE

1. Conclusion

For this project, the cryptocurrency market was first examined to better understand patterns involving volatility, correlation, and structure. Other considerations are; great fluctuation in the market, high level of correlation and Bitcoin dominating the market. The first two approaches, namely hierarchical clustering and Minimum Spanning Tree (MST) offered insights on clustering of crypto-currencies to enhance portfolio diversification and also provide deeper insights on system risk. The information gathered here is useful for intelligent capital investment and management of risks.

2. Future Scope

Possible future work includes but not limited to: combination of real-time data processing and prediction model with market trend prediction. Second, macroeconomic variables, sentiment analysis, and new cryptocurrencies contribute extra value when the study extends its range. Its usefulness would rise if such studies employed a variety of forms of machine learning including anomaly detection or adaptive portfolio optimization

CASE STUDIES

1. "Long-Range Trends in the Cryptocurrency Market"

Objectives:

Research the fluctuation of long-range value of cryptocurrencies along the periods of its existence.

Evaluate market efficiency based on the Hurst exponent as the explication of the scheme.

For this purpose, non-overlapping windows should be applied to assess dynamic variations in the market with time.

Models and Methods Used:

Hurst Exponent Calculation: Used to determine the persistence or whether a series is anti persistent or purely random over time.

Rescaled Range Analysis (R/S) and Detrended Fluctuation Analysis (DFA): Used to estimate the Hurst exponent of the cryptocurrency returns.

Comparison of mean items and coefficients from the first precrisis time window and the total sample period, as well as the first and second consecutive non overlapping time windows.

Conclusion:

Random walk hypothesis dominates the cryptocurrency market due to high efficiency of the market and unpredictability of such returns.

Some of the cryptocurrencies underwent persistence or mean reversion at specific windows further capturing the time variation in the crypto market.

The market also continues to be unpredictable and fairly risky still, thus requiring more elaborate approaches to its analysis and more prudential procedures when it comes to investment.

2. "Transitions in the Cryptocurrency Market During the COVID-19 Pandemic" -

Objective: To investigate the impact of the COVID-19 pandemic on the cryptocurrency market dynamics.

To analyze market transitions using network analysis to understand synchronization and centrality among cryptocurrencies.

To determine the phases of market recovery post-pandemic shock.

Data and Methodology

:Network Analysis: Cryptocurrencies were modeled as nodes with links representing correlations between their returns.

- The winner-takes-all approach was applied to focus on strong correlations.
- Centrality measures such as degree centrality and betweenness centrality were used to identify the most influential cryptocurrencies and periods of market synchronization.
- Dynamic Correlation Networks: These networks were generated using rolling
 15-day windows to observe temporal changes in market structure.

Conclusion: The cryptocurrency market experienced significant synchronization during the financial panic (March 12, 2020–April 1, 2020) but quickly transitioned back to its initial state by July 2020.

High synchronization during the panic suggested limited diversification opportunities, while the recovery highlighted market resilience.

The findings emphasize the importance of dynamic analysis methods to capture transient phenomena, which static approaches might overlook

3. "A_Network_Analysis_of_the_Cryptocurrency_Market"

"- Prof. Adel Ismail Al-Alawi, Naser Alshakhoori.

Objectives: In the research, various techniques of network analysis will be

employed, employing the cryptocurrency market as the object of analysis to

evaluate dependencies or cryptocurrency entailing dependencies. Specifically,

it employs:

Hierarchical tree Minimum Spanning Tree (MST) approach to categorize and

rank assets in a tree structure using the daily returns of correlation coefficient,

known as Pearson.

Dendrogram through the means of hierarchical approach to cluster

cryptocurrencies and their market trends.

Models Used: Models

The study employs:

Minimum Spanning Tree (MST):

Firmly links all cryptocurrencies in such a way that the sum of distances

between them is minimal given the correlation matrix.

Discovers the composition and dominance of cryptocurrencies in the market.

Hierarchical Dendrogram:

Group cryptocurrencies by location and their characteristics of their market

behavior and identifies major player in the market.

Conclusion:

Ethereum emerged as the main cryptocurrency as predictions that Bitcoin

would be more prominent than it were wrong.

The popularity of Ethereum is an explanation by its usefulness in conducting

ICOs (Initial Coin Offerings) and as ground for other virtual currencies.

Network Clustering:

The hierarchical analysis puts the cryptocurrencies into layers with different

dependency coefficients. Bitcoin was isolated in a group; which showed that

its behavior was different than the normal cryptocurrencies.

Implications for Investors:

24

The analysis provides a view of the relationships between assets that can be used to diversify and optimize a portfolio as well as to see market trends.

Novelty:

The present study examines relationships within the cryptocurrency market based on the network approach as such a viewpoint may be important and prompt additional analysis.

REFERENCES

- 1. "Long-Range Trends in the Cryptocurrency Market" (2020) M. Nabipour, P. Nayyeri, H. Jabani, A. Mosavi, E. Salwana, Shahab S.
- 2. "Transitions in the Cryptocurrency Market During the COVID-19 Pandemi" (2021)- Mojtaba Nabipour, Pooyan Nayyeri, Hamed Jabani, Shahab S., Amir Mosavi.
- 3. "A_Network_Analysis_of_the_Cryptocurrency_Market" (2021)- Suresh Ramakrishnan, Agha Amad Nabi, Melati Ahmad Anaur.

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