OULUN AMMATTIKORKEAKOULU

Kristian Ratia

TECHNICAL ANALYSIS IN CRYPTOCURRENCY TRADING

A Historical and Analytical Investigation

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Kristian Ratia
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Oulun ammattikorkeakoulu

ABSTRACT
Oulu University of Applied Sciences
Data Analytics and Project Management

Author: Kristian Ratia
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This thesis research how technical analysis performs on cryptocurrencies. Some basic methods were tested on multiple currencies in different categories. The tested currencies were not the most popular ones because there were too much data on the most popular currencies for the scope of this research. Basic methods were tested on some most used settings. Every technique was tested alone. After testing, methods were compared with each other, and also different currencies were compared.

Keywords: Technical analysis, cryptocurrency, blockchain

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TERMS

Blockchain: A decentralised and distributed ledger technology that enables secure and transparent transactions on a peer-to-peer network.

Cryptocurrency: A digital or virtual currency that uses cryptography for security and operates independently of a central bank.

Technical analysis: A method of analysing market trends and patterns using historical price and volume data.

Moving averages: A technical analysis tool that calculates the average price of a security over a specific period, used to identify trends and potential entry and exit points.

Relative strength index (RSI): A momentum oscillator that measures the speed and change of price movements to identify overbought and oversold conditions.

Bollinger Bands: A technical analysis tool that measures volatility by plotting two standard deviations away from a moving average, used to identify potential breakouts or trend reversals.

Payments: A category of cryptocurrencies designed primarily to facilitate transactions and payments.

Privacy: A category of cryptocurrencies designed to provide enhanced privacy and anonymity for users.

Gaming: A category of cryptocurrencies that are designed for use in online gaming and virtual worlds.

Cross-border payments: A category of cryptocurrencies facilitating cross-border transactions and remittances.

Liquidity: The ease with which an asset can be bought or sold without affecting its price.

Volatility: The degree of variation in the price of an asset over time.

Market sentiment: The overall attitude or outlook of investors towards a particular market or asset.

Fundamental analysis: A method of analysing the underlying financial and economic factors that affect the value of an asset.

Regulatory changes: Changes to laws and regulations that may affect the legality or regulation of a particular market or asset.

Decred (DCR): a cryptocurrency that uses a hybrid consensus algorithm of Proof-of-Work and Proof-of-Stake to secure its network and validate transactions. It aims to be a self-governing and community-driven platform for decentralised applications' governance, development, and management.

High-Performance Blockchain (HPB): a blockchain platform that aims to solve traditional blockchain networks' scalability and performance issues. It uses software and hardware improvements to achieve high transaction throughput and low latency.

Hive (HIVE): a blockchain-based social media platform that aims to provide users with a decentralised and censorship-resistant alternative to traditional social media platforms. It is built on the Steem blockchain but with crucial improvements and modifications.

Paris Saint-Germain Fan Token (PSG): a cryptocurrency representing fan tokens of the Paris Saint-Germain football club. It allows fans to participate in club-related decisions and events through fan-voting systems and rewards.

Yield Guild Games (YGG): a decentralised gaming platform that allows players to earn cryptocurrency by playing blockchain-based games. It also allows players to own and trade in-game assets and virtual real estate.

ICON (ICX): a blockchain platform that aims to connect different blockchain networks and allow them to interact seamlessly. It uses its consensus algorithm, Loop Fault Tolerance (LFT), to ensure the security and reliability of its network.

ARPA Chain (ARPA): a privacy-focused blockchain platform that aims to provide secure and private computation for businesses and individuals. Cryptographic technologies and smart contracts enable secure data sharing and computation.

A new kind of Network (NKN): a blockchain-based platform that aims to provide a decentralised and scalable communication and data transmission infrastructure. It uses a unique consensus algorithm, Proof-of-Relay, to ensure high network throughput and low latency.

Celo (CELO): a blockchain platform that aims to provide a more inclusive and accessible financial system through mobile-first applications and decentralised finance (DeFi) protocols. It uses a novel consensus algorithm called Proof-of-Stake with identity (PoS+), which aims to be more energy-efficient and decentralised than traditional PoS algorithms.

Jasmy (JASMY): a blockchain platform that aims to provide businesses with a decentralised and transparent supply chain management system. It allows businesses to track and verify their products throughout the supply chain using blockchain technology.

Audius (AUDIO): a blockchain-based platform that aims to provide a decentralised and censorship-resistant music streaming service. It allows artists to upload their music directly to the platform and earn cryptocurrency from streaming and tipping.

Litentry (LIT): a decentralised identity verification platform that aims to provide individuals and businesses with a secure and transparent identity system. It allows users to manage their identities across different blockchain networks and applications.

Synthetix (SNX): a decentralised synthetic asset platform that allows users to trade various synthetic assets, such as fiat currencies, commodities, and cryptocurrencies, on the blockchain. It uses its token (SNX) to incentivise users to participate in the network and collateralise their synthetic assets.

Monero (XMR): a privacy-focused cryptocurrency that uses advanced cryptographic techniques to ensure the anonymity and confidentiality of its users' transactions.

A token: a digital asset created on top of the existing blockchain network.

1 INTRODUCTION

1.1 Background of the study

The blockchain concept was introduced in 1991 by Stuart Haber and W. Scott Stornetta(Haber and Stornetta, 1991). The research introduced a method for securely recording the time and date when a digital document was created, modified or accessed.
A person or group called Satoshi Nakamoto used the same principles and released the "Bitcoin: A Peer-to-Peer electronic Cash System" whitepaper in 2008. The paper introduced a concept of decentralised digital currency, which would work without banks or payment processors. Instead of an official institute that controls Bitcoin, an extensive network ensures all the transactions are valid. As long as no-one has more than 50% of the calculation power of the network or there is no bug in the code, all the transactions are secured. Every transaction is added to the pool of transactions. The network will add transactions from the pool to the Bitcoin blocks. Block has all the needed information of new transactions and previous block hash. Now if someone tried to change the previous block, the hash of the block would change, and all the blocks after that should be calculated again. If the calculation power is less than 50% of the network's power(Sayeed and Marco-Gisbert, 2019), then the person or group who changed the information would never get the needed calculations done in time. At some point, the network would abandon the changed branch of blocks because there is a newer branch on the network.

The first considerable media coverage of Bitcoin was in 2013. At the beginning of 2013, Bitcoin's value was $13.5, and at the end of the year value was $750. The highest value was $1 150(statmuse, 2013). That year there was a lot of news about Bitcoin, making it more widespread. Ten years from that cryptomarket has grown enormously. Today there are 22 932 different cryptocurrencies, but only 9127 are active (forbes, 2023). The total market cap of cryptocurrencies has grown to $1.1 trillion in ten years. Still, it has also come down $2 trillion in the last two years.

As previous numbers show, the cryptocurrency market is very volatile. Values can change a lot, even in a short time. When investing in cryptocurrencies, there is a high reward and risk. When prices change a lot, it is difficult for investors to know whether they should buy more, sell, or hold their current investment. However, there are some techniques for reducing risks. One of the ways is to use technical analysis on cryptocurrencies.

Technical analysis uses historical price data to predict the value in the future. Technical analysis is not a new method. In 1688 De la Vega wrote a book about the stock market. De la Vega's book described how charts and price patterns could predict future prices (De la Vega, 1688). Even though De la Vega did not use the term technical analysis, that book is still considered the first technical analysis book. Methods have been developing since the beginning of the technical analysis. Nowadays, computers can analyse a massive amount of data, and calculations can be much more complex than in the beginning.

Data plays a big part in technical analysis. Getting data from cryptocurrency's current and past values is relatively easy. Many cryptocurrency exchanges list past values. Binance is one cryptocurrency marketplace where anyone can download past data (Binance, 2023). Binance list data from all coins that can be traded on the Binance service, and there are more than two years of data free to download. The amount of data Binance offers is more than enough for technical analyses. In this research, Binance data is used. Binance list all the trading pairs on different CSV files. Csv-files have all the trades on separate lines. Lines have the identifier of trade, the current price of the currency, quantity of trade, the total value of trade, timestamp, information if the trade was a maker and indicator if the transaction is completed. Price and total value are determined based on the trading pair and can be another cryptocurrency or real currency. Cryptocurrencies researched in this research used USD as trading pair.

1.2 Research problem and research question

This research measures how well fundamental technical analysis works on some cryptocurrencies. The timeline of the research is 1.1.2022 to 15.4.2023. The result might not be valid in the different market situations or on the cryptocurrencies not researched in this paper. This research gives some basic technical analysis information and a brief history of blockchain, cryptocurrencies and technical analysis. There is also some information about other analysing methods which could be used for analysing the future price of cryptocurrencies.

2 BLOCKCHAIN

2.1 Blockchain technology

Not many elements are needed for a basic version of blockchain. Blockchain has blocks linked together chronologically (Alman and Hirsh, 2019). Each block, except the first one, has a link to the previous block. Blocks have one or more transfer data inside them. That data has a timestamp, information about the transfer and nonce. Nonce is a short text added to the block to get the correct hash. When the block has all the needed data, it will be hashed. When the block is hashed on the proof of work type blockchain, the function will try to find a hash, which, for example, has the first six numbers as 1. If the beginning of the hash does not have the right amount of number ones, then the nonce is changed, and the block will be hashed again. That loop will continue until the hash has the right amount of one's in the beginning. Finding a nonce that will give a hash that the network will approve is very resource-consuming, but checking later on if the hash is correct is trivial(Danial etc., 2022).

How many first numbers must be one depends on the calculation power of the network. The numbers needed are constantly modified to keep the calculation hard enough but not too hard. Hashing ensures that the chain of blocks can not be modified later. If someone changes anything from the past block, then the hash of that block would not be correct. It would need to be calculated again. The next block has the information of the previous block hash; if it changes, that block would need to be calculated again. That would go through the whole list of blocks. That means that if someone wants to change any information, it is necessary to calculate every block that comes after the changed block. If the person who tries to make a change has less than 50% of the calculation power of the whole network, the person cannot calculate blocks again fast enough. Network notice that there is a branch which has different content than the other actual branch. Then network checkouts which branch is more extended. At the time, both can be as long, but if the person who made a change has less calculation power than all the others, then when time goes by, the actual branch will be bigger and bigger, and eventually, it will be longer than the modified branch. At that point, the network will no longer share the modified branch because the network will destroy the shorter branch. If the deleted branch had transactions not in the more extensive branch, those transactions would return to the transactions pool.

2.2 History of blockchain technology

Blockchain technology is not an entirely new technology. There are a lot of parts which are invented before and used in blockchain. One of those is the Merkle tree. The Merkle tree has an essential role in blockchains. It was invented in 1970 by Ralph Merkle (US Patent 4, 1982). On the Merkle tree, each block is hashed, then paired with another block and hashed again. That will continue until every block has been hashed and paired. This structure ensures that data is the same as the original. Therefore, Merkle trees have an essential role in verifying data on a blockchain. With the Merkle tree, it is easy to detect if any of the data has been changed, no matter how much there are data.

Another essential part of the blockchain is hash chains. It was introduced in 1991 by Stuart Haber and W. Scott Stornetta (Haber and Stornetta, 1991). Hash chain is a technology where hashes are linked together. Before hashing the current content, the previous hash will be added to the content, and after that, everything is hashed. So if someone tries to change anything on the chain, all the hashes after the change are wrong, and those would be needed to hash again.

Decentralisation has an essential role in blockchain. Technology does not need to be decentralised, but many blockchains are decentralised. The advantage of decentralisation is that no single institute controls the blockchain. On a decentralised blockchain, anyone can access the full node of the blockchain and verify every transaction made. On centralised systems, users have to trust the institute controlling the blockchain. The whole blockchain might disappear if the controller gets hacked or goes bankrupt.

Peer-to-Peer (P2P) is a network without a central server. Every computer connected to the network also works as a server. When P2P was invented, data could be downloaded without a centralised server. Downloading became more efficient because people could download part of the same data from multiple users. The speed did not anymore depend on the speed of the server.

P2P technology is utilised for blockchain as no centralised authority is needed to validate transfers. Blockchain allows users to make transactions directly with one another. Instead of the need for central trust authority, blockchain uses a consensus mechanism for secure transactions. Every device, part of the blockchain network, works together to make secure transactions. The network makes a public ledger where anyone can check any of the transfers made in the history of the blockchain network (Sandra and Alman, 2019).

Satoshi Nakamoto published a whitepaper on Bitcoin in 2008 (Nakamoto, 2008). It is not public information if Nakamoto is a person or if it is a group of people. Instead, the whitepaper describes how Bitcoin works. Bitcoin uses blockchain technology and has a decentralised public ledger. Bitcoin is just one implementation of blockchain, but because it was the first to get considerable publicity, it has been used as an example of the development of many other blockchains.

The financial sector was among the first to recognise blockchain's potential(Polyviou, Velanas and Soldatos, 2019). The transfer must be secure when moving money or any asset from one place to another. Blockchain offers secure transfer for peer-to-peer transfers. Some people do not trust banks as much as they trust blockchain. Payments are easy to implement on a blockchain. Only a few essential data are needed on every transfer: who pays to whom and the amount. After it had been proved that blockchain works in the financial sector and the knowledge of blockchain increased, some people began to research blockchain possibilities in other sectors. There is still a lot to research in many sectors, but blockchain could be helpful in at least the following sectors: supply chain management, healthcare, identity management and voting.

Transactions in the financial sector must be secured, but if Bitcoin failed, it would not change anything. All it would have caused would be some money lost on trial. Other sectors are different things. Those sectors do have working systems already, just like the financial sector had before Bitcoin, but the difference is that they do not want to have multiple systems simultaneously. For example, if supply chain management adds blockchain to their system, they no longer want to use their current system. Healthcare and identity management has also working systems already; because of their data, they do not want to have that same data on multiple systems. Therefore it is harder to use blockchain on those systems. For example, in Finland, healthcare is more likely to become one giant system than multiple small ones, which makes it even harder to use blockchain in healthcare. The basic system has always been used in the finance sector, and Bitcoin and other cryptocurrencies have been on the side, adding more transfer possibilities. Both systems have worked at the same time and will still work.

2.3 Types of blockchain

Bitcoin is an example of a blockchain designed for secured Bitcoin transactions. Bitcoin blockchain only saves the data needed for transactions and cannot save anything else. Ethereum was the first blockchain which introduced decentralised applications (dApps). Ethereum blockchain can be used for smart contracts and saving data(Besancon, etc., 2022). For example, it allows artists to save their work as digital art. Anyone can own a copy of digital art, but blockchain proves who owns the original copy of the art(Radermecker and Ginsburgh, 2023).

Same way than anyone can have a poster of a famous painting, but only one can have the original painting.

2.4 Advantages and disadvantages of blockchain technology

Changing data once saved on the blockchain is difficult (Aponte-Novoa, Orozco, Villanueva-Polanco and Wightman, 2021). Data can be changed if there is consensus from most blockchain networks. Getting that consensus for unauthorised changes is practically impossible when the blockchain is big enough. Modifying past transactions would require more computing power than anyone can access. Still, it is possible in theory, but it would be tough. Each participant on the blockchain network has a copy of the entire blockchain, which makes it hard to change. The decentralisation structure makes blockchain transparent; anyone can track and verify every transaction. Transactions have timestamps, and they are linked to previous transactions, which makes an audit trail and reduces the possibilities of fraud, manipulation or errors on the chain.

Blockchain does have some disadvantages. A decentralised and secure system needs more resources than a centralised one. Blockchain networks consume enormous amounts of space, network bandwidth and calculation power(Dorri, Kanhere, Jurdak and Gauravaram, 2019).

3 CRYPTOCURRENCIES

Cryptocurrency can be defined in several different ways(Pernice and Scott, 2021). In this research, cryptocurrency has been defined in the way that it is an asset with a ledger and cryptographic abilities. Therefore, in theory, it can be used as a currency. People can transfer different cryptocurrencies to others, but only Bitcoin is widely used for paying for goods. Even with Bitcoin, companies make more trials on how the payments with that would work instead of using it as an actual payment option. "Cryptocurrencies seem likely to find use for certain kinds of transactions, such as international money transfers and buying drugs, but not for day-to-day transactions, at least not for a decade or two." (Kirkby, 2018). Cryptocurrencies differ from traditional currency because they do not have a physical copy. All the real currencies have a physical version, even though most of the money is only digital. In some cases, cryptocurrencies have a public ledger, and anyone can download all the transactions to see if they are valid.

3.1 History of cryptocurrencies

Bitcoin is considered as the first cryptocurrency. After Bitcoin, there have been a lot of different cryptocurrencies, and more are coming all the time(Sabry, Labda, Erbad and Malluhi, 2020). Most new cryptocurrencies try to do some things better than Bitcoin or any other cryptocurrency. The areas that are tried to improve are (at least) energy efficiency, transaction speed and transaction price (Levy, 2019).

3.2 Types of cryptocurrencies

If defining cryptocurrency is not trivial, putting different cryptocurrencies into different categories is even more complicated. There are no specific categories for cryptocurrencies, but currencies can be arranged into categories by the main properties of the currency(Arooj, Farooq, Umer, 2022). One possibility for categories is payment, privacy, randomcoins, decentralised finance, gaming and cross-border. (coingecko, 2023). Because cryptocurrencies are more or less a copy of the other cryptocurrencies, those categories are not perfect, and most cryptocurrencies could be a member of several categories. There can be more categories, but those listed once are used in this research. Deciding which category currency belongs to is even more challenging when using more categories.

3.3 Overview of cryptocurrencies

This research has divided cryptocurrencies into ten different categories, explained in this chapter. Cryptocurrencies used in this research were chosen to be the currency's popularity. The most popular ones had to leave out of the research because the size of the files, which listed all the trading between 1.1.2022 to 15.4.2023, was too big. Only file sizes below 3GB were used. Bitcoin example would have been an exciting currency for research, but the size of the Bitcoin trade file was more than 80GB, which was way too big to handle efficiently on the used hardware. Currencies were chosen as a way that they present all the categories.

3.3.1 Payments

Payment is a category that has cryptocurrencies which primary use is payment. These coins have fast transaction times and low fees. Those abilities make these currencies potential competitors for credit cards and bank transfers. In this category, two coins are studied: Celo and Stellar Lumens.

Celo is a mobile-first blockchain platform. Celo aims to provide financial services all over the world to anyone. Celo is designed to be fast, cheap and easy to use(celo).

Stellar Lumens (XLM) is designed for cross-border payments. The Stellar network allows fast and low-cost transactions between different currencies, making it an excellent alternative for international money transfers(Stellar).

3.3.2 Smart Contracts

Smart contracts are designed to support smart contracts functionality. These are networks where it is possible to save video, text, images, sounds, files or smart contracts. Smart contracts are

self-executing contracts with the agreement term in the blockchain code. In this research, this category has four coins: Uniswap, Waves, Decred and ARPA chain.
Uniswap (UNI) is a platform for trading cryptocurrencies and other digital assets. The uni swap platform allows UNI token holders to vote on proposed changes and upgrades to the platform.
Waves are blockchain platform that aims to be easy for developers to create and deploy decentralised applications (dApps). It has a user-friendly interface and programming language called RIDE. With RIDE, it is easy to write smart contracts. In addition, wave tokens are used for transactions(uniswap).
Decred (DRC) is a cryptocurrency designed for more democratic and decentralised governance than other cryptocurrencies. DCR holders can vote on proposals to change the network's rules and settings(decred).
ARPA Chain (ARPA) is a platform designed for privacy-preserving computation. It allows users to share data and computations without revealing sensitive information. In addition, an ARPA token is used to pay for the service(arpanetwork).

3.3.3 Privacy

Privacy currencies have been developed to protect users' privacy and anonymity. On some cryptocurrencies, all the transfer data is publicly available. Some privacy currencies hide user identities and transfer details. In this research have been studied XMR and ZEC.
XMR (Monero) uses advanced cryptographic techniques to protect the privacy and anonymity of users. As a result, XMR transactions are entirely private and cannot be tracked(getmonero, 2023).
ZEC (Zcash) lets users choose fully transparent or private transactions(z.cash, 2023).

3.3.4 random coins

Random coins are not a natural category. It is used to get one category with random coins instead of the same kind of currencies. This research has studied the following random coins: Paris Saint-Germain Fan Token, Litentry, Synthetix and Aave.
Paris Saint-German Fan Token(PSG) is designed for the fans of the Paris Saint-Germain football club to interact with the team and earn rewards. The token is built on the Chiliz platform. With tokens, fans can participate in club-related polls, games and competitions(fantoken).

Litentry(LIT) aims to provide a secure and efficient way to verify user identities on the blockchain. The platform uses a reputation-based system which allows users to control their data and privacy. Synthetix (SNX) allows users to trade stocks, commodities and cryptocurrencies. The platform allows users to create and trade assets without a centralised intermediary(litentry, 2023).
Aave (AAVE) is a decentralised lending platform which allows users to borrow and lend cryptocurrencies. The platform uses collateralised and flash loans for fast, efficient borrowing and lending(aave).

3.3.5 Decentralised Finance (DeFi)

Decentralised Finance platforms are designed to be decentralised, transparent, and accessible to anyone with an internet connection. The most common use case for DeFi is lending and borrowing. Smart contracts and collateral are used to ensure the loans are repaid. Another use case is to allow users to exchange cryptocurrencies without the need for centralised exchange. Instead, decentralised exchanges operate peer—to—peer basis, using often automated market-making algorithms to ensure liquidity and fair prices. In this research, CAKE is studied as an example of DeFi.
Cake(CAKE) is a native cryptocurrency on PancakeSwap decentralised exchange. PancakeSwap is a place where users can exchange a lot of different cryptocurrencies. On centralised exchanges, users can only exchange cryptocurrencies that the exchange has decided to exchange. On PancakeSwap, anyone can add a new cryptocurrency or token available to trade. On some currencies in PancakeSwap, users cannot be sure if they are pure scams or just new currencies with a good team behind them and if they are designed to be real cryptocurrencies someday(bitscreener, 2023).

3.3.6 Gaming

Cryptocurrencies in the gaming category are designed for the use of games. Games have tried a new monetising model where players can buy or get as a reward from achievements or by winning non-fungible tokens (NFTs). NFTs are one way to increase players' commitment to the game or to the group of games which use the same NFTs. Yield Guild Games and Smooth Love Potion have been researched in this research.

Yield Guild Games (YGG) is used in the game Axie Infinity. Players can collect, breed, and trade creatures called Axies in the game. Creatures are represented as NFTs. Players can earn cryptocurrency by playing the game and winning battles(yieldguild, 2021).
Smooth Love Potion (SLP) is also related to Axie Infinity. SLP is an in-game currency used for breeding and creating new Axies. Players can buy SLP by trading it on cryptocurrency exchanges or earn it by winning battles(axieinfinity, 2021).

3.3.7 Cross-Border Payments

Cross-Border Payments are designed for payments which go from one country to another. Special needs for this kind of payment are speed and low fees. This research has studied two currencies: ICON and the New Kind of Network.
ICON(ICX) network allows different blockchains to communicate with each other via smart contracts. ICON is also a token used for transaction fees and fees of the platform(icon).
A New Kind of Network(NKN) aims to create a decentralised, secure communication infrastructure for the Internet. NKN uses novel consensus mechanisms, which are called Proof of Relay. It rewards nodes for providing reliable high-speed connectivity. NKN is a cryptocurrency on the network, and it is used for transaction fees and governance on the platform(nkn, 2020).

3.3.8 Energy Efficiency

There has been a lot of debate about bitcoins' energy consumption (Das etc., 2020). That is because mining uses a lot of energy (de Vries and Alex 2020), which is why some blockchains have been designed to be much more energy efficient. In this research, there has been studied HBAR.
HBAR is a native token in the network called Hedera Hashgraph. The network aims to provide fast and efficient transactions. The hashgraph consensus mechanism is more energy efficient than the proof-of-work mechanism(hedera, 2018).

3.3.9 Internet of Things (IoT)

Internet of Things cryptocurrency category refers to blockchain technology to enable secure and efficient communication between IoT devices. This category has multiple use cases: smart home devices, industrial sensors, autonomous vehicles and supply chain management. In this research, IOTA was researched in this category.

IOTA aims to provide fast, secure, and efficient transfers between devices. IOTA uses Tangle, which enables feeless transactions and scalable network growth(iota, 2023).

3.3.10 Social Media

The Social Media category has cryptocurrencies that are used in social media platforms and on platforms which are not designed for social media but have some communication possibilities. One example of that kind of platform is Steem which is designed for gaming but has some user interactions. In this research, there have been studied Jasmine, Hive and Audius.

Jasmine(JASMY) aims to provide a secure and efficient payment solution for consumers and businesses (Jasmy, 2023) (jasmincapital, 2023).

Hive(HIVE) uses blockchain technology to provide censorship-resistant, transparent content creation and sharing platforms(hive, 2020).

Audius(AUDIO) is a decentralised music streaming platform allowing artists to share and monetise their content without the traditional music industry(audius, 2020).

3.4 Advantages and disadvantages of cryptocurrencies

In the beginning, cryptocurrencies were invented for decentralised transfers with no central authority that would control the currency's value. Therefore, there was no need to have any trust in the system as traditional currency has. With traditional currency, central banks can control the currency's value by printing more money or destroying money. With cryptocurrency, no one can control the value directly(Qaroush, Zakarneh and Dawabsheh, 2022). It is based on the popularity of currency. Other advantages of cryptocurrencies are lower transaction fees, greater accessibility and increased security.

The disadvantages of cryptocurrencies are high volatility, limited acceptance and scams. There is no central authority which controls the value of cryptocurrencies. That makes the value to be very volatile. Value can rise or drop a massive amount in a short time. Some people invest in cryptocurrencies, and when central authorities make decisions that affect the value of money, that will impact the value of cryptocurrencies via investors. Investors might need to liquidise their assets, and when many investors sell their assets, the asset's value will drop. Cryptocurrencies are not a currency in the way that standard currencies are. With official currency, people know their money is good in one or more countries. With cryptocurrencies, people must check every store one by one do they accept payments with cryptocurrencies. Because cryptocurrency wallets can be anonymous, using them for scams is easier than using bank accounts. With bank accounts, scammers must ensure the transfers do not trace back to them using a mediator or other systems which hide that money goes to the scammer. With cryptocurrencies, scammers can have their wallet, which does not have any proof of who is the person or group behind the wallet. Getting money back from the scammer might be more challenging than regular bank transfers. Scammers have also used people's greediness and lack of knowledge about cryptocurrencies. There have been many scams where people have invested in cryptocurrencies without knowledge, hoping for big profits. Sometimes, money goes directly to the scammer(Kerr, Loveland, Smith and Smith, 2023).

3.5 Technical analysis

With technical analysis, investors can predict the future of the markets(Ayala etc., 2021). Technical analysis has been used as long as there have been stock markets. Technical analysis analyses the market data and identifies patterns and trends. The primary assumption of technical analysis is that trends will repeat their actions. Technical analysis is not perfect for predicting the future. It is more of a tool for making better investment decisions. Investors should always know the current situation and not follow the technical analysis unthinkingly. Past market data is not proof of coming market values.

3.6 Types of technical analysis

Technical analysis can be divided into the following methods: chart patterns, technical indicators and candlestick analysis(Carlson, Dickson, Knudsen and Tatro, 2011). Chart patterns are visual presentations of the assets' value and market movements. A chart pattern is used for visualising the trends. Technical indicators are mathematics calculations used for identifying trends. Technical indicators can be used with trading bots because they are not visual. Instead, they are numbers that computers can compare. In this research, technical indicators are used. Candlestick is another visual analyse method. Instead of a single pricepoint, like in a chart pattern, a candlestick reveals the period's lowest, highest, starting and ending price.

3.7 Advantages and disadvantages of technical analysis

The advantage of technical analysis is better knowledge of the market. Without any technical analysis, investors only know the asset's current price. Technical analysis also offers investors an objective approach to the asset value. Investing without any objective data is more or less just guessing. With technical analysis, investors have at least a reason to buy or sell the assets. If the decision is wrong, the investor can change strategy to make investing more profitable next time. A disadvantage of technical analysis is that investors might trust technical analysis too much. Technical analysis is not always correct, and trusting too much on technical analysis might be unprofitable(Rockefeller, 2020).

4 THEORY OF MARKETS

4.1 Efficient-market hypothesis

The efficient-market hypothesis (EMH) is a hypothesis that state that assets price reflect all available information(Niroomand, Metghalchi and Hajilee, 2020). That theorem implies that it is impossible consistently to outperform the asset market because all the available information already reflects the asset's price.

The idea behind EMH is that the market is efficient. There are three forms of EMH: weak, semi-strong and strong. The weak form states that all the past information is in the current prices. Therefore analysing past prices does not give any advantages to investors. Semi-strong states that all publicly available information is in the current prices. Finally, the strong form states that all information, including insider information, is in the current prices, and no information could benefit an investor.

EHM states that technical analysis or any other analysis using past prices or other public information would be useless because all the information would be on the current price. There is a debate among researcher does the market work efficiently. Even if all the information from the assets could be calculated on the prices, there is no way to calculate every event in the world to the prices. Wars, pandemics, new inventions and research results will affect the current markets, and at least some events are not so easily predicted.

If technical analysis works perfectly, then anyone using it will buy assets until the price is the same as in the future. After that, everyone would sell the asset until the price is as low as it will be. Unfortunately, that is not the case; therefore, technical analysis does not always predict the future. The cryptocurrency market is not closed, and real-world events will affect it. Unpredicted events may affect a lot for the price of any investments. Many investors make decisions just by feeling (Yongkil and Dongyeon, 2020). Technical analysis works best in the market, with many investors not using technical or other analysis before investing decisions.

4.2 Behavioural Finance

Another way to predict any asset's future value is to use behavioural finance(Ballis and Verousis, 2022). In behavioural finance, psychology and other social science are used to understand better investors' behaviour and how that behaviour affects the markets. Investors are not always rational and do not always make the best possible investing decisions. There are many vital biases which explain this behaviour, including overconfidence, loss aversion, and herding behaviour

According to EMH theory, technical analysis does not work because whatever it reveals about future prices is already in the current price. On the other hand, according to behavioural finance theory, technical analysis works perfectly in the market. That is because when investors use feelings when making decisions, it is possible to calculate where they will invest and how an asset's value will change.

The efficient market hypothesis and behavioural finance provide an essential theoretical view of the market's work. It is necessary to understand how the market works to make suitable investments. The more information, the more likely it is to make good investment decisions. Understanding market behaviour and why other investors make their investment decisions is vital. This research is about technical analysis, but knowing more about market behaviour is also essential.

5 DATA AND METHODS

5.1 Research design

The research design on this research is experimental. The same technical analysis methods are used with different settings on the same data. Therefore, there is no exact answer to which technical analysis method or which settings on which cryptocurrency would be the best. In any asset market, there can not be a simple answer which works best because market situations change too much, and different methods and settings perform differently in different market situations. For example, suppose the technical analysis is used for real investment. In that case, the market must constantly research to determine what method or setting will perform best in the current situation.

5.2 Experimental design

The amount of technical analysis methods and settings is endless. Also, the amount of cryptocurrencies is tremendous. In this research, the most basic methods of technical analysis have been used in the most common settings. Choosing methods and settings might not be the best possible, but finding the best methods and settings is very time-consuming because even the best method at the time might perform worst in the future. In this research, cryptocurrencies are divided into ten categories. Categories are chosen by the currency's primary purpose and by the design of the currency. Categories are not official, and most coins could be in multiple categories. Multiple currencies have been chosen for each category to understand better how well technical analysis works on different categories. Still, there is a considerable possibility that chosen currencies do not present the current category in the best possible way, and the results do not present the category's results.

5.3 Data collecting

In this research, publicity data has been used to calculate how well different technical analysis methods perform. All the data has been downloaded from the Binance cryptocurrency platform. Binance is the largest cryptocurrency exchange platform (coinmarketcap, 2023) when measuring by 24h trading volume. Therefore, Binance offers a lot of publicly available data. Binance lists cryptocurrency trades as trading pairs. In Binance, people can change their cryptocurrencies to another or traditional currency. Therefore, Binance offers a good amount of data for all trading pairs. This research uses only cryptocurrencies with USDT trading pairs to get compatible results. Some of the chosen currencies had traded from longer timelines than others. For comparison, all the chosen currencies' trade records have been cut, and all trades before 1.1.2022 have been removed.

Binance has 154 different cryptocurrencies (Binance, List of Supported Assets, 2023). Every cryptocurrency can be traded in one or more currencies. For example, most of the cryptocurrencies can be traded with USDT.

There are a lot of past trades available on the Binance website. Trades are listed as CSV files. Files have lines like "15539817, 444.05900000, 1.20000000, 532.87080000, 1615334400412, False, True". That line explained is:

- 15539817 is the identifier for the trade
- 444.05900000 is the price of the cryptocurrency
- 1.20000000 is the amount of cryptocurrency in the trade
- 532.87080000 is the total value of the trade
- 1615334400412 is the timestamp of the trade
- False indicates if the trade is maker or taker
- True indicates whether the trade has matched or executed

Maker means a trader offers to buy or sell at a specific price. Taker means that trader buys or sells at the price someone else offers. Usually, takers pay more transaction fees than makers. In some cases, the maker does not pay any transaction fees.

For this research, only trading pairs which had USDT were used. The total amount of data where USDT was another pair was 589GB when this research was done. That data is all about text. The approximate amount of data was 8.4 billion trades. More popular currencies had more data available. Bitcoin is the most popular cryptocurrency, and the amount of bitcoin-USDT trading pair data was 83 GB or about 1.2 billion trades.

5.4 Data analysis

Cryptocurrencies have been analysed by making a Python code, which used TA-lib (github, 2023). Some technical analysis methods need more time and historical data than others. All the methods have been tested for compassion in the way that analysing begins from 1.1.2022. After 200 days of analysing data, the code will invest if the current method sees that it is a good time for investing and selling if the method predicts that the market price will be lower. For more realistic results code will trade only $1000 at the time, and after the trade, it will not make another trade in the next minute. A trading fee is a small payment which goes to the cryptocurrency marketplace. In this research trade fee was defined to be 0.075%. The same trade fee was used on every trade and every technical analysis method. The code defined starting money as $100 000, but the amount would not significantly affect the results. If starting money is less than the amount of the most extensive possible trade ($1000), the code could always trade all the money. That can be a realistic situation when the available money for investing is small, but it is not realistic if it is big enough. When trading significant amounts of money, there are not enough sellers or buyers available, and the trader will affect the currency's price. Trading will always affect the price, but in this research, it is estimated that $1000 once a minute does not affect the price too much on the market, and the results are pretty realistic.

5.5 Technical analysis methods

In this research, the most common basic technical analysis methods have been used. Used methods were Bollinger Bands, Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI) and Simple Moving Average (SMA). All of the methods were tested on different settings.

5.5.1 Bollinger Bands

John Bollinger developed the Bolling Bands method in the 1980s. (Day etc., 2023). Bollinger bands have three lines: upper, middle, and lower. The distance between the upper and lower bands shows volatility. When bands are far away, volatility is higher than when bands are close. When the middle band touches or crosses the upper band, the currency is considered oversold and indicates a buy signal. When the middle band touches or crosses the lower band, it is considered that currency is overbought and indicates a sell signal.

Bollinger bands were used as following settings:

- value of periods were 20, 21 and 22
- value of standard deviation were 2, 2.5 and 3
- moving average type were simple moving average(SMA), exponential moving average (EMA) and weighted moving average(WMA)

5.5.2 Simple Moving Average(SMA)

SMA is used for identifying trends in the price. SMA is calculated by calculating the average price of the period(Svetunkov and Petropoulos, 2018). When the current price is above average, it is considered a buying signal; when it is below average, it is considered a selling signal.

SMA is a method used to calculate the average asset price at a specific time. In this research, SMA is used with the following settings:

- "10 0 20 0"
- "50 0 100 0"
- "50 0 200 0"
- "20 0 50 0"
- "10 0 50 0"

The first number is the number of periods. The second number is shift or offset. The third number is used for calculating the upper band of the Bollinger Bands indicator. Finally, the fourth number is used to calculate the lower band of the Bollinger Bands indicator.

5.5.3 Exponential Moving Average (EMA)

EMA is like SMA. The difference is that in EMA, recent prices weigh more than older prices. That makes EMA more responsible for changes than SMA. It is not clear which one is better for market prediction. EMA will get changes faster, but slower reactions to signal might also mean that the reaction is more accurate(Investopedia, 2023). When SMA reacts to the signal, the signal is more vital.

There are four settings on EMA: the number of periods grouped for calculation. EMA cannot be calculated if the timeline has fewer periods than in this setting. The second number presents offset. Offset is used for shifting EMA left or right. Offset is used when a trader wants to know how the indicator would look in the future or the past. In this research, offset has not been used. The third setting is the smoothing factor. It presents the number of periods used to smooth the EMA. Smoothing factors reduce noise and short-term changes. The fourth setting is offset for the smoothing factor. It has not been used in this research. The settings used in this research are:

- "10 0 20 0"
- "50 0 100 0"
- "50 0 200 0"
- "20 0 50 0"
- "10 0 50 0"

5.5.4 Moving Average Convergence Diverge (MACD)

MACD is calculated by subtracting the longer EMA from the shorter EMA and then comparing that to the shortest EMA used for the signal line(fidelity, 2023). For example, a typical setting for MACD is subtracting 26-period EMA from 12-period EMA and comparing that to the 9-period EMA. When the calculated MACD line crosses the signal line and is above it, it is a signal to buy. When it falls below the line, it indicates a sell signal.

On the moving average, there are three settings. The first number represents the periods for calculating a fast exponential Moving Average (EMA). The second number indicates the number of periods used for calculating slower-moving EMA. The third number represents the number of periods used for calculating the signal line. The MACD is calculated by subtracting slow EMA from fast EMA. The settings used in this research are:

- "12 26 9"
- "5 35 5"
- "8 17 9"
- "7 14 7"

- "21 55 8"
- "10 20 5"
- "10 30 5"
- "15 30 5"
- "18 35 6"
- "6 13 5"

5.5.5 Relative Strength Index(RSI)

RSI differs from the previous indicators because it is only one number, not the line. The RSI indicator is a number between 0 – 100. RSI is calculated using formula RSI = 100 – (100/[1 + {14-Day Average Gain/14-Day Average Loss}])(stockcharts, 2023). In common cases, the market is considered oversold when the value is over 70 and overbought when the value is below 30. If the value is over 50, it indicates an uptrend; when it is below 50, it indicates a downtrend.

RSI is calculated as the ratio of the average profit over the average loss at the amount of chosen periods. Then the result is scaled to 0 – 100. Typically, if the scaled number is less than 30, it is considered an oversold market; if the number is more than 70, it is considered an overbought market. This research used RSI as setting 7, 14 and 21.

5.6 Data visualisation

All the data could be visualised using charts, but there is no need for visualisation when data is used for paper trading and testing methods of technical analysis. This research concentrates more on how well technically analysed methods work and how they could be used in automatic trading. If these methods are used in actual trading, then there would be a benefit to visualise the results. When visualising results, it would be easier for humans to follow strategies and see if strategies work as they should. Because there is no visualisation, there might be errors in paper trading. That must be considered if the result of this research is applied to actual trading.

6 RESULTS

Calculations were made by the program, which first had $100000 starting capital. The first program calculated different technical analyses for 200 days. After that program invested the money if it was a good time to invest according to the selected method and sold if it was an excellent time to sell according to the selected method. For more realistic calculations program only buy or sell $1000 per minute. A small amount at the time does not affect the price. As much as $100000 at the time would affect it. On some cryptocurrencies, results would be realistic even with a much higher investing amount, but for the best result which can be compared, the same rules have been used for all cryptocurrencies. The program also takes a 0.075% fee on every trade. Even though the fee amount is relatively small, it makes a significant difference when trading a lot of trades. For example, when the amount of trade is $1000, the trade fee is $0.75. On 80000 trades, it makes a $60000 difference in the results. That is a significant difference.

According to the method, the program sold only when it was an excellent time to sell. A stop-loss method should be initialised if the intention is to make as good a result as possible. The stop-loss method will sell the asset if the value drops a certain amount, or it may also sell if the asset price goes up a certain amount. Selling if the value drops protect the investor when technical analysis does not notice the asset going down. Stop-loss limits might be a 1%-5% down limit and a 2%-10% upper limit. The down limit is essential to ensure the loss is not too significant. The upper limit ensures a profit will be made if the price increases. The upper limit does cut some profits, but it might make more money in the long run because technical analysis methods will not see the price going down before it is too late. There is also a moving down limit. On that down limit is the first selected percentage below buying price. If the price increases, a new down limit is selected percentage below the highest price. Moving down the limit does not go lower. It stays at the same or goes higher. It will activate whenever the price is down the selected percentage from the highest price. For the best knowledge of how well different technical analysis performs, it was important not to have stop-loss because the actual performance could be measured that way.

6.1 Analysis of cryptocurrency market trends

The timeline of the research was 1.1.2022 to 15.4.2023. At the time world had just recovered from Covid-19. "On February 24, 2022, Russia launched a full-scale invasion of Ukraine" (Bucken-Knapp and Sildre, 2022)—both affected the world's finances deeply.

At the beginning of the research value of cryptocurrency market capitalisation was $2.2 trillion. At the end of June, market capitalisation had dropped below $900 billion. Today market capitalisation is $1.2 billion (coinmarketcap, 2023). With the timeline researched in this research, the market mainly was going down or staying at same. This research does not present how technical analysis would work in a market situation where the market value would increase. A couple of years earlier, there was considerable growth in the market, but it was over before the timeline of this research. For information on how technical analysis would work in different market situations, there would need to be another research on the different market situations. Because market situations change constantly, new cryptocurrencies come to market, and people have different valuable options more critical than others, it is impossible to do research which would tell how well different technical analysis methods would work in different situations. Therefore trend analysing is only a tool, not a method which would predict the future always right.

Nevertheless, trend analysis is an essential tool when analysing the future of cryptocurrencies. It gives valuable information to the trader. With that information, traders can reduce risks and make better profits or at least reduce losses.

6.2 Overall performance

The average performance of all used currencies with all tested technical analysis methods was -44 898,71. Median performance was -61 754,83.

Average	-44898,71
Median	-61754,83
Max	99861,71
Min	-97292,69

Table 1

As seen in Table 1, overall performance was not good at selected currencies, selected technical analysis methods and selected timeline. The median performance of all the cryptocurrencies and all the technical analysis methods and settings was -61%. That is a huge loss because the timeline when trades were made was only about 270 days. The best performance of all was +99% which is an excellent result. The average annual return from the stock market is 2%-8% (McGrattan and Prescott, 2003). Compared to that, 99% is a considerable amount. These results can be seen as an example of how volatile cryptocurrencies are, but they can also be seen as an example of technical analysis not working well. Average and median performance does show that all the technical analyses are not working well. At least the trading fee makes it impossible to profit just by taking random currencies and using random technical analysis.

6.2.1 Technical analysis methods

			Compared to all
Average of All	Average	-42394,58	
	Median	-49816,43	
	Max	53979,65	
	Min	-92618,85	
Bollinger	Average	-45039,74	-2645,16
	Median	-61900,73	-12084,31
	Max	99861,71	45882,06
	Min	-95521,30	-2902,45
EMA	Average	-43888,84	-1494,25
	Median	-48520,48	1295,94
	Max	72340,53	18360,88
	Min	-97292,69	-4673,84
Macd	Average	-50820,78	-8426,20
	Median	-54533,82	-4717,40
	Max	15337,00	-38642,65
	Min	-87555,09	5063,76
RSI	Average	-29448,77	12945,82
	Median	-40669,70	9146,72
	Max	44398,95	-9580,70
	Min	-90105,99	2512,85
SMA	Average	-42774,79	-380,21
	Median	-43457,39	6359,04
	Max	37960,05	-16019,60
	Min	-92619,17	-0,32

Table 2 shows the performance of different technical analysis methods

As seen in Table 2, all the selected methods were mostly unprofitable. The median loss was 49%. Because of the trade fee, this result shows that using technical analysis and paying the fee was not profitable in the current market. These results might be different in other market situations, but it needs another research to measure how these technical analysis methods would work in different market situations. The median performance of all the strategies was unprofitable. According to the results, knowing some technical analysis knowledge is vital. Without knowledge, it is more likely to lose money than make a profit. Even the best performer, RSI, was unprofitable. Bollinger bands make the best maximum profit, but the median result was -62%. That means Bollinger bands do not work on every currency, situation or setting. The maximum result might be a good value if the person who uses technical analysis knows how technical analysis works and knows what the best settings are. Without knowing why the maximum performance is as good as it is, it is useless to know the best performance. It is better to see median performance than maximum or average performance without knowledge. If only one strategy with one setting is used, half of the cases' performance is better than the median performance and half of the cases' performance is not as good as the median performance. The average does not tell what profit or loss is expected if only one of the settings is used.

6.2.2 Bollinger bands

Period	STD	Type	average	median	max	min
20	2	0	-46206,78	-61984,44	84399,18	-95521,30
20	2	1	-46315,61	-61998,45	86634,49	-95521,30
20	2	2	-45981,72	-61879,74	87363,85	-95521,30
20	2,5	0	-44868,71	-61929,67	87367,59	-95521,30
20	2,5	1	-45286,34	-61894,08	88210,30	-95521,30
20	2,5	2	-45130,74	-61835,90	88870,56	-95521,30
20	3	0	-43994,31	-62116,17	93375,29	-95521,30
20	3	1	-44312,57	-61942,55	89650,69	-95521,30
20	3	2	-44260,40	-61947,09	90608,98	-95521,30
21	2	0	-46078,44	-61883,34	85052,69	-95520,58
21	2	1	-46225,20	-61748,22	86926,44	-95520,58
21	2	2	-45918,03	-61920,48	86944,60	-95520,58

21	2,5	0	-44819,63	-61797,64	87906,93	-95520,58
21	2,5	1	-45171,87	-61868,69	88794,65	-95520,58
21	2,5	2	-45047,91	-61831,32	88763,85	-95520,58
21	3	0	-43759,78	-62103,37	96863,97	-95520,58
21	3	1	-44302,78	-62007,30	87983,30	-95520,58
21	3	2	-44138,40	-61946,87	91100,00	-95520,58
22	2	0	-46009,39	-61757,30	85584,43	-95515,30
22	2	1	-46184,95	-61631,61	86548,59	-95515,30
22	2	2	-45820,81	-61685,17	87650,89	-95515,30
22	2,5	0	-44595,00	-61797,44	88401,22	-95515,30
22	2,5	1	-45065,67	-61879,30	88671,06	-95515,30
22	2,5	2	-44991,96	-61817,80	88791,06	-95515,30
22	3	0	-43487,87	-62112,57	99861,71	-95515,30
22	3	1	-44160,50	-62022,20	88141,40	-95515,30
22	3	2	-43937,63	-61958,48	91818,48	-95515,30

Table 3, Bollinger bands performance on different settings

The maximum performance of Bollinger Bands was best in every setting. However, average and median performance was not nearly as good as the maximum. A closer investigation shows that Bollinger bands made a profit only on the following currencies: DRC, Arpa and Zec. Every other currency was unprofitable. The reason why only those three currencies were profitable is unknown. A closer investigation of profitable currencies revealed no good reason Bollinger bands made profitable trades with them. Later on in this research, those currencies are analysed more precisely. A common thing about those currencies was that their values rose and dropped on the researched timeline. Most of the currencies' values were much higher at the beginning of the timeline than at the end.

Interestingly, Bollinger band made the best profit along all the tested technical analysis methods on those three currencies. On the Bollinger bands setting, the moving average type has three options: 0 for simple moving average (SMA), 1 for exponential moving average (EMA) and 2 for weighted moving average (WMA). Slight differences exist between moving average types, but differences are not significantly different.

6.2.3 EMA

Period	Average	Median	Max	Min
5	-42446,57	-47647,84	72340,53	-95647,66

10	-41178,43	-46098,41	53236,11	-94013,05
20	-42110,12	-46439,36	59937,08	-94287,17
50	-45834,52	-56944,43	30188,12	-95959,21
100	-46254,45	-49259,79	67140,54	-97292,69
200	-45508,95	-49906,20	66373,00	-95576,14

Table 4, EMA performance in different periods

EMA was profitable with XMR, DRC and partly on lit. On EMA settings, there were no significant differences on different settings. On the median, period 50 worked much worse than others, but the average profit was as bad as in every other setting. The worst performances were relatively the same in all settings. Based on this research, there is no difference between the number of periods. Five to twenty periods seem to perform slightly better than a hundred or two hundred, but the difference is insignificant.

6.2.4 MACD

fast	slow	signal	average	median	max	min
5	35	5	-51621,18	-54014,84	-8410,45	-84151,58
6	13	5	-48826,90	-48019,32	-10129,13	-81020,32
7	14	7	-54065,93	-55987,25	-19687,60	-85981,79
8	17	9	-55606,96	-59758,11	-14408,13	-87395,32
10	20	5	-54643,55	-59285,65	-11227,54	-87555,09
10	30	5	-53084,96	-53113,74	-5094,02	-84125,42
12	26	9	-53242,29	-52702,59	-20122,23	-81936,14
15	30	5	-51421,75	-53203,39	-15099,56	-82302,58
18	35	6	-45952,83	-51284,07	15337,00	-82930,32
21	55	8	-39741,48	-42950,87	5223,14	-84067,51

Table 5, MACD performance on different settings

In this research, MACD was run by giving three numbers: fast period, slow period and signal period. The fast period is the number of periods used for calculating fast EMA. For more sensitive MACD lines, fast periods should be short. A slow period calculates long-term price trends. It would have been better to research also short-term price changes and signals alone in this research. That would push the scope of the research even further, and on this scope, both were researched simultaneously. That is not good for performance, but overall performance did not differ much from other technical analysis methods. On MACD, there is a significant difference in performance on different settings: Average profit is -from -40% to -56%, and median profit is from -43% to -60%. MACD was profitable only on two settings, 21,55,8 and 18,35,6. There is no logic in the results. It is impossible to say what is the best setting. According to this result, luck affects the result more than the setting itself. It does not matter the value of fast, slow or signal setting. This research does not reveal which is the best MACD setting.

6.2.5 RSI

period	average	median	max	min
7	-39149,99	-44802,93	28827,69	-90105,99
14	-31573,09	-37350,86	31714,22	-86443,27
21	-17623,23	-17354,58	44398,95	-77578,38

Table 6, RSI performance in different periods

Of all the researched methods, RSI performed best. It was the most profitable method. However, there was a considerable difference between different amounts of periods. RSI was calculated using 7, 14 and 21 periods. Twenty-one periods performed best only -18%, and seven performed worst -39%. For subsequent research, there should be research on how RSI performs if the number of periods is even longer. This research calculated RSI only using three different amounts of periods. Based on that, it is impossible to say if the performance is better with more periods or if it is just randomly in the order of the number of periods. In this research, RSI had values of 30 for the lower limit and 70 for the upper limit. When examining RSI's performance on single currencies more carefully, it seems that it is just a coincidence that on this table, performances are in the way that seven is the worst and 21 is the best. That is because there are different kinds of orders on single currencies.

6.2.6 SMA

		average	median	max	min
10	20	-46970,72	-52022,03	16762,61	-90082,88
10	50	-40314,99	-44949,84	14949,35	-87567,29
20	50	-38264,35	-43038,74	30953,01	-85844,44
50	100	-35629,82	-37592,14	37960,05	-88424,41

50	200	-52694,08	-61226,87	21879,90	-92619,17

Table 8, SMA performance on different settings

SMA average performance is from -36% to -52%, and median performance is from -38% to -61%. The maximum profit amount is insignificant, but the loss is 92% in the worst cases. According to this research, it cannot be said that SMAs' performance would be predictable. The difference between worst and best performance is quite significant. Jasmy was the only currency where SMA performed well. It was profitable on that. However, there is no apparent reason why it was profitable on Jasmy but unprofitable on every other currency. Jasmy does not differ much on every other currency. One difference is that Jasmy began on much higher and dropped faster to the end value than others. After Jasmyäs value dropper, it was pretty much the same to the end. Many other currencies' values did rise in the middle of the timeline.

6.2.7 All categories

Cells in Appendix 2 are calculated so that the sum of all lines is 0. If the number is positive, that currency performed better than others. If the number is negative, that currency performed worse than others. Most methods performed better in the random and privacy categories than others, but as seen in Appendix 1, trades were still unprofitable. There were huge differences between the performance of the different categories. According to this research, Privacy-category could be a better category for using technical analysis on trading than others. There were only two currencies in the privacy category, which means that results might be based on randomness instead of the quality of technical analysis. Notable information is that the privacy and random categories currencies were not profitable. Both were unprofitably, but technical analysis methods were not as unprofitably as in other categories.

6.2.8 Cryptocurrencies on Payments-category

	Average	Median	Max	Min
All	-62168,60	-67040,75	-7513,32	-84067,51
Bollinger	-67132,15	-67160,49	-61092,32	-73446,65
EMA	-54270,28	-56619,85	-21190,30	-79083,67
Macd	-70345,02	-70562,93	-45497,38	-84067,51

RSI	-38838,80	-41118,92	-7513,32	-78264,32
SMA	-42488,46	-42798,40	-14733,50	-64733,97

Table 11 Technical analysis Methods performance in the payments category

The payments category had two currencies: Celo and XLM. The performance was entirely unprofitable. Even the best-performed analysis RSI and SMA was unprofitable with about -40%. Other analysis profits were from -54% to -70%.

Table 12, Celo value

Table 13, XLM value

Both Celo and XLM value was about 25% at the end, compared to the beginning. It clearly shows that the timeline of the research was quite bad. There was a massive downswing in the value at the time. Even though these two graphs are only for two currencies, the same results are seen on other currencies later in this research.

6.2.9 Cryptocurrencies on Smart Contracts-category

	Average	Median	Max	Min
All	-16351,21	-10183,11	99861,71	-95647,66
Bollinger	1685,42	-348,55	99861,71	-82474,22
EMA	-33303,42	-30713,04	67140,54	-95647,66
Macd	-42725,06	-40685,81	15337,00	-68797,54
RSI	-17143,14	-13269,72	30806,23	-85427,30
SMA	-40183,50	-36043,84	37960,05	-88424,41

Table 14 Technical analysis methods performance on category

The intelligent contracts category has four currencies: Uniswap, Waves, Decred and ARPA chain. Performance was unprofitably, but much better than in the payments category. The average profit with Bollinger bands was positive. Even though Bollinger bands' average profit was profitable, it was not much profitable, only 1,68%. Bollinger bands maximum profit was enormous. Starting capital was almost doubled. However, median profits were negative, which means that most of the Bollinger bands settings were unprofitable.

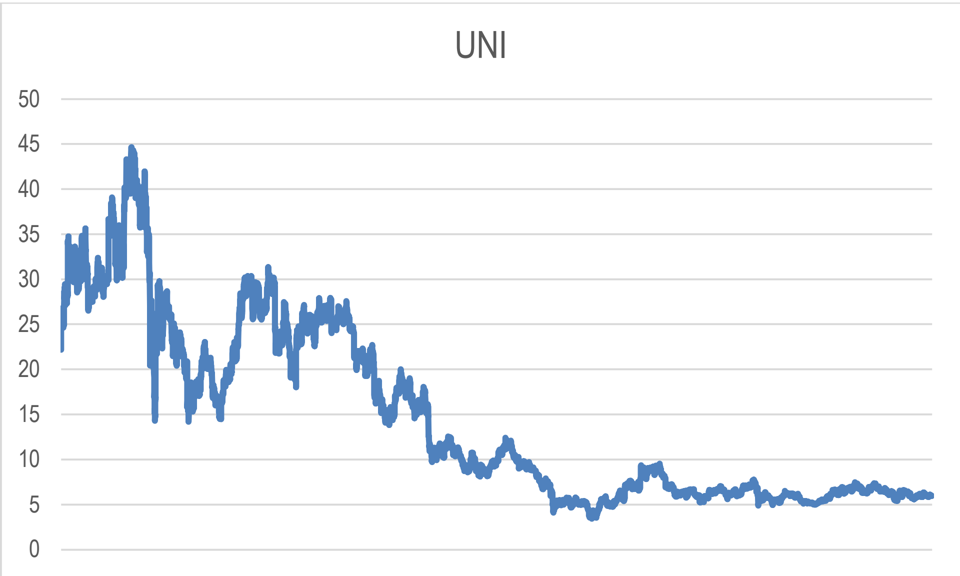

Table 15, Uniswap value

Table 16, Wave value

Wave did have a massive spike in the middle of the timeline. The value rose from 10 to 60 and returned to below ten at the short timeline. These kinds of spikes are pretty typical in cryptocurrency markets. Sometimes they are pump and dump schema (Nghiem, Muric, Morstatter and Ferrara, 2021). Pump and dump is a situation where one or more people buy currency. Then, after that, they make some hype around the currency so the price will go higher. Then, after the price is higher, they sell and make some profit. Because the total value of some currencies is relatively low, pump and dump can be done on those just by buying a lot of currency. Technical analysis is terrible at the pump and dump schema because the technical analysis does not think about why the price change. It just reacts to the new price. Without closer examining the Wave currency, it cannot be said if that spike was the pump and dump schema or if it was something else. That kind of spike can come from many different reasons. For example, one reason could be rumours that currency would be listed on some significant exchange, and then the listing does not happen. The reason for the spike is not in the scope of this research.

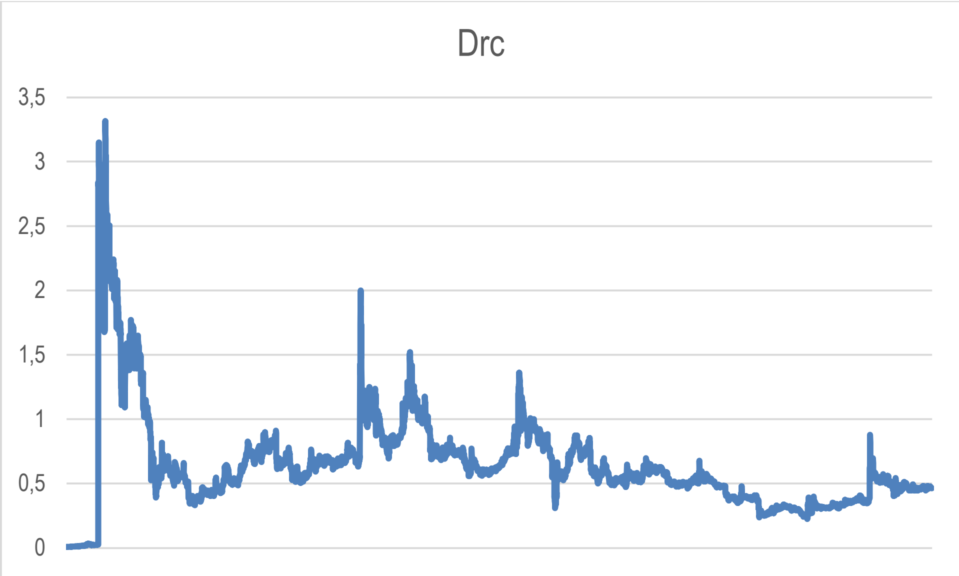

Table 17, Decred value

Decred performed best on all the researched currencies. That might be because the initial value was 0.006198, and the highest value was 3.315. That means that the value rises 53000% in the short time at the beginning of the timeline. However, after that value dropped 86%, the reason for that high volatility is unknown and would need more research. For performance measuring that high volatility is not good. If the program did buy at the beginning and sold after that, it would profit greatly, but it does not say if the algorithm would be profitable in the long run when the price is more steady.

Table 18, Arpa value

Arpe's value also went up in the middle of the timeline. The best value was almost five times the value of the beginning. Then the value gets back to the same value as the beginning. These kinds of situations should be pretty good for technical analysis. At least it is easy to see later on when would have been an excellent time to buy and when it would have been a good time to sell. That might be why Arpa performed better than many other currencies. Based on this research, it seems that Bollinger Bands is one of the best performers in the situations like this. Then again, whether that was only randomness or whether Bollinger Bands is excellent in this situation is unclear.

6.2.10 Cryptocurrencies on Privacy-category

	Average	Median	Max	Min
All	-10794,00	-3852,29	59937,08	-49854,90
Bollinger	-4273,73	-4585,99	22208,80	-30694,06
EMA	-5851,40	-6444,79	59937,08	-49768,74
Macd	-28444,70	-29086,94	-5094,02	-49854,90
RSI	-6385,45	-5951,27	31714,22	-42759,33
SMA	-19278,26	-23527,92	5681,39	-35437,66

Table 19 Technical analysis Methods performance in the Privacy category

The privacy category had two currencies: Monero and Zcash. Performance was negative, but not much in some cases. Bollinger, Ema and RSI were less than 10% negative. Macd and SMA performed worst.

Table 20, Monero value

Table 21, ZCash value

On closer research, EMA and RSI performed well on Monero and Bollinger Bands performed well on Zcash. However, the research does not reveal why those performed well and other technical analysis methods did not. Moreover, both of these currencies were pretty much volatile all the time, except for the last third of the timeline. That kind of change in the price could have been seen in better results on all the technical analysis methods, but it did not.

6.2.11 Cryptocurrencies on random coins-category

	Average	Median	Max	Min
All	-52677,92	-66847,07	72340,53	-76657,68
Bollinger	-66378,86	-67519,93	-51951,15	-76538,25
EMA	-33312,71	-39956,11	72340,53	-66249,54
Macd	-44947,21	-47384,73	5223,14	-70873,73
RSI	-7873,60	-2623,00	44398,95	-51677,56
SMA	-44275,16	-47847,95	2220,93	-76657,68

Table 22 Technical analysis methods performance in the random coins category

The random coins category had four currencies: Paris Saint-German Fan token, Litentry, Synthetix and Aave. However, almost half of the investment would have gone on most technical analysis methods.

Table 23, Paris Saint-German value

Table 24, Litentry value

Table 25, Synthetix value

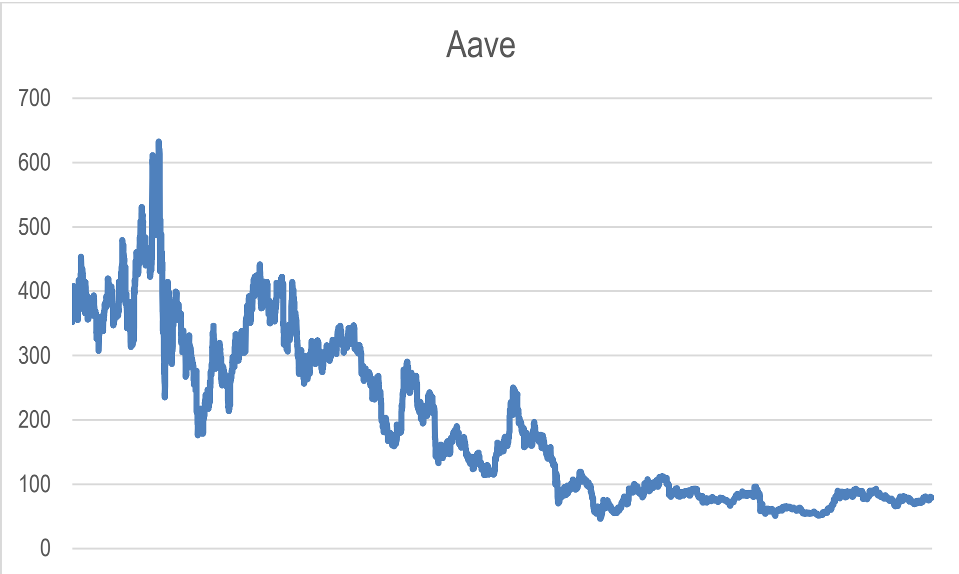

Table 26, Aave value

6.2.12 Cryptocurrencies on Decentralised Finance (DeFi) -category

	Average	Median	Max	Min
All	-69932,06	-83754,41	-13430,89	-84182,76
Bollinger	-84042,94	-84120,63	-83705,97	-84182,76
EMA	-69933,98	-69524,86	-63950,41	-77234,91
Macd	-55326,31	-56091,89	-45077,42	-62057,38
RSI	-44455,90	-44212,03	-34092,53	-55063,13
SMA	-38228,19	-43140,27	-13430,89	-56305,25

table 27 Technical analysis Methods performance in the Decentralised Finance category

In the Decentralised Finance category, there was only Cake currency researched. This result tells only how well technical analysis was performed on Cake. More research would be needed to determine how methods would perform on different DeFi currencies. On Cake, methods did not perform well. Average performance was -69%, and Bollinger Bands was -84%.

Table 28, Cake value

6.2.13 Cryptocurrencies on Gaming-category

	Average	Median	Max	Min
All	-83388,96	-91476,89	-22663,42	-97292,69
Bollinger	-91487,75	-91488,89	-87438,49	-95521,30
EMA	-85748,02	-85404,74	-71965,25	-97292,69
Macd	-69539,56	-69913,49	-52978,36	-87555,09
RSI	-66116,01	-71416,42	-22663,42	-90105,99
SMA	-74887,13	-72470,15	-48047,65	-92619,17

Table 29 Technical analysis Methods performance in the Gaming category

The gaming category had two currencies: Yield Guild Games and Smooth Love Potion. Both are from the same game. The value of the currencies in the gaming category does not depend only on investors. Price will rise if the game becomes more popular and dive if it loses players. Value does not depend entirely on the game, but the game's popularity will affect the value. In the future, it would be great to see some currencies used on multiple games; therefore, a single game would not affect the currency's value so much. The gaming category had the worst performance in technical analysis of all the categories. The average profit was -83%. The best performer was again RSI, but even that performed severely, getting -69% profit. Technical analysis methods had not been designed to predict the popularity of games, but it does not necessarily mean that currencies could not be rightfully analysed with technical analysis methods. For better results, research is needed for another time and more currencies in this category.

Table 30, Yield Guild Games value

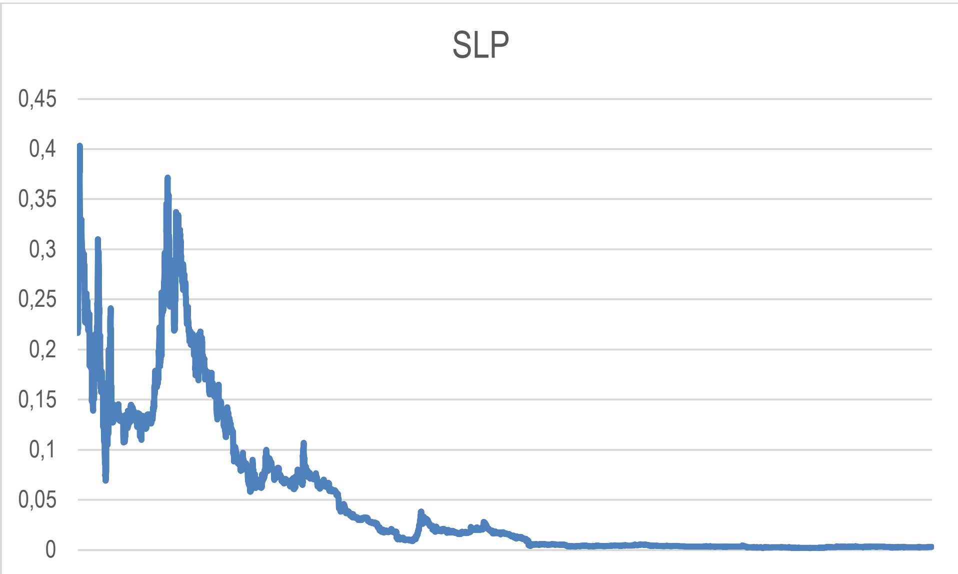

Table 31, Smooth Love Potion value

A hacker stole $625 million on March 23. 2022(The Verge, Mavis, 2022), but that did not affect the values of YGG and SLP. That might affect the players' interest in the currencies, but the game currencies might have dropped anyway. It is hard to say why the currency value went down. It might also be just the timeline because most of the currencies' value goes down on the selected timeline.

6.2.14 Cryptocurrencies on Cross-Border Payments-category

	Average	Median	Max	Min
All	-46292,45	-45613,89	17815,24	-84441,20
Bollinger	-44992,16	-45196,16	-39493,78	-51243,66
EMA	-37169,91	-36197,16	-17249,59	-64212,00
Macd	-56177,19	-56886,03	-25158,93	-69798,66
RSI	-35095,09	-34248,10	17815,24	-71016,56
SMA	-51210,06	-46059,53	-38027,47	-84441,20

Table 32 Technical analysis Methods performance in the Cross-Border Payments category

In the Cross-Border Payments category, there were ICON and New Kind of Network currencies. In this category, methods performed exceptionally well compared to many other categories, but still, the results were negative. The average profit was -46%. The best result was RSI, and it was 18% profit. The average and median were very unprofitably, so it does not matter that maximum were profitable.

Table 33, Icon value

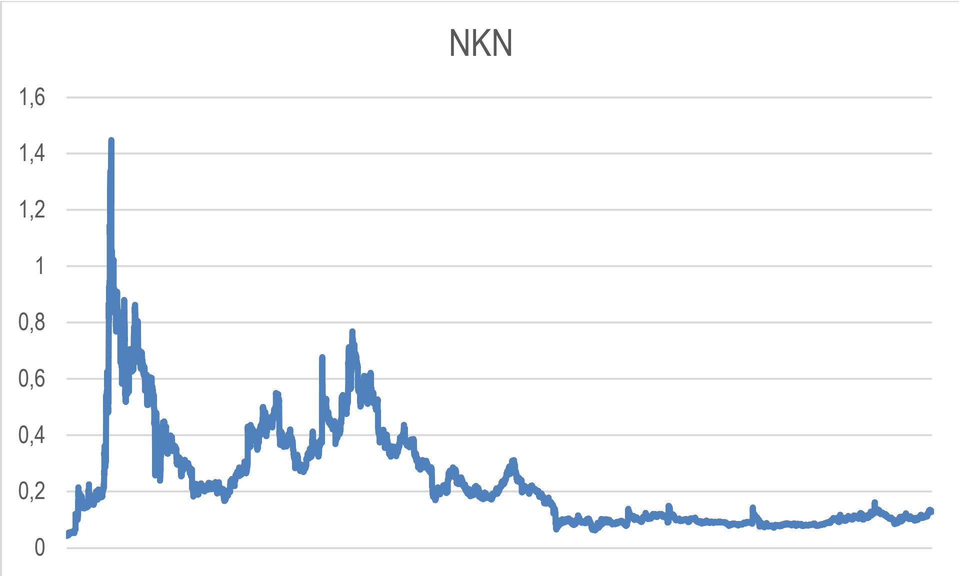

Table 34, New Kind of Network Value

Both currencies in the Cross-border payments category were in a good situation before half of the timeline, and after that, both values stayed quite the same. Therefore, technical analysis should perform well at the beginning of both currencies because the values change significantly, but none of the technical analysis methods was profitable.

6.2.15 Cryptocurrencies on Energy Efficiency-category

	Average	Median	Max	Min
All	-64947,06	-64878,57	-41951,17	-81416,96
Bollinger	-65038,40	-64878,57	-64100,82	-66755,68
EMA	-59274,47	-59623,59	-43397,85	-71810,08
Macd	-68709,29	-71715,52	-41951,17	-81416,96
RSI	-73645,33	-74150,86	-69206,76	-77578,38
SMA	-58517,49	-54813,74	-51992,49	-70933,96

Table 35 Technical analysis Methods performance in the Energy efficiency category

In the energy efficiency category, only one currency was researched: HBAR. Performance was once again terrible. The average profit was -65%. The best result was -42%, which was the worst best result of all categories.

Table 36, HBar value

6.2.16 Cryptocurrencies on Internet of Things (IoT) -category

	Average	Median	Max	Min
All	-61704,29	-62192,55	-39998,38	-80544,71
Bollinger	-62267,80	-62192,55	-62005,57	-62795,24
EMA	-52571,83	-52175,62	-46731,69	-59640,98
Macd	-67797,24	-70173,05	-49337,37	-73923,45
RSI	-55643,92	-53214,65	-52799,52	-60917,59
SMA	-61070,64	-63231,97	-39998,38	-80544,71

Table 37 Technical analysis Methods performance in the Internet of Things category

In the Internet of Things category, only IOTA was researched. The average result was -62%. None of the results were positive.

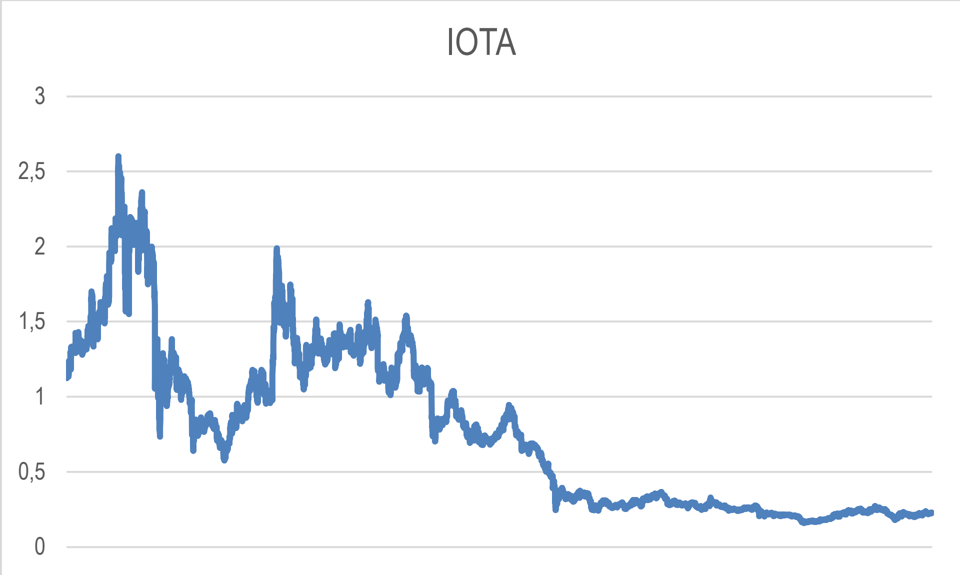

Table 38, IOTA value

6.2.17 Cryptocurrencies in Social Media-category

	Average	Median	Max	Min
All	-36594,54	-33636,37	34414,69	-82823,50
Bollinger	-34993,26	-33636,37	-14335,20	-57729,16
EMA	-50410,15	-57702,63	1492,73	-77260,07
Macd	-42174,13	-39376,42	-3875,43	-75687,99
RSI	-27063,39	-47356,09	34414,69	-64170,88
SMA	-23222,20	13265,39	30953,01	-82823,50

Table 39 Technical analysis methods performance in the Social media category

Three currencies were researched in the Social media category: Jasmine, Hive and Audius. Methods performed much better than many other categories. The average profit was -37%. Still a huge loss, but it could be worse. Median SMA results were profitable.

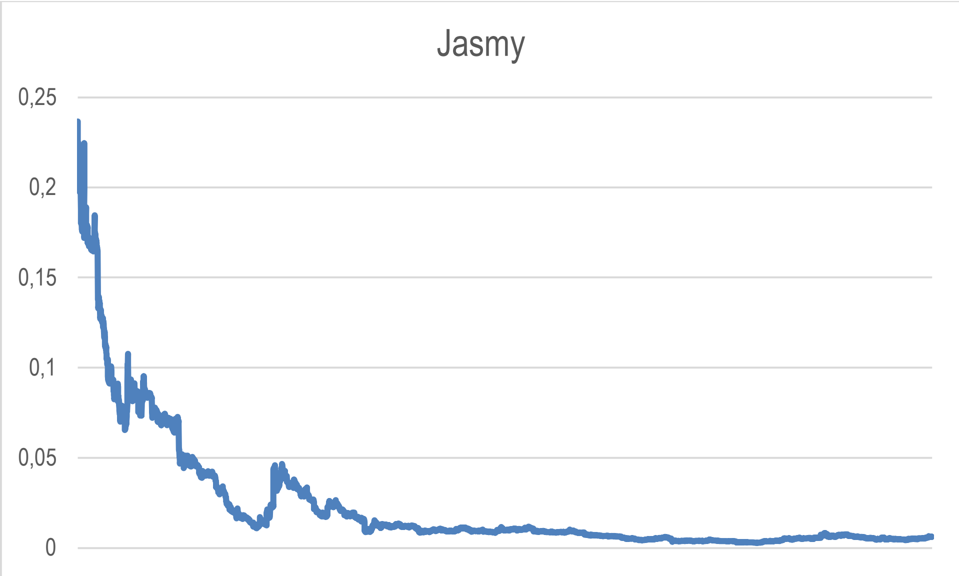

Table 40, Jasmine's value

Table 41, Hive value

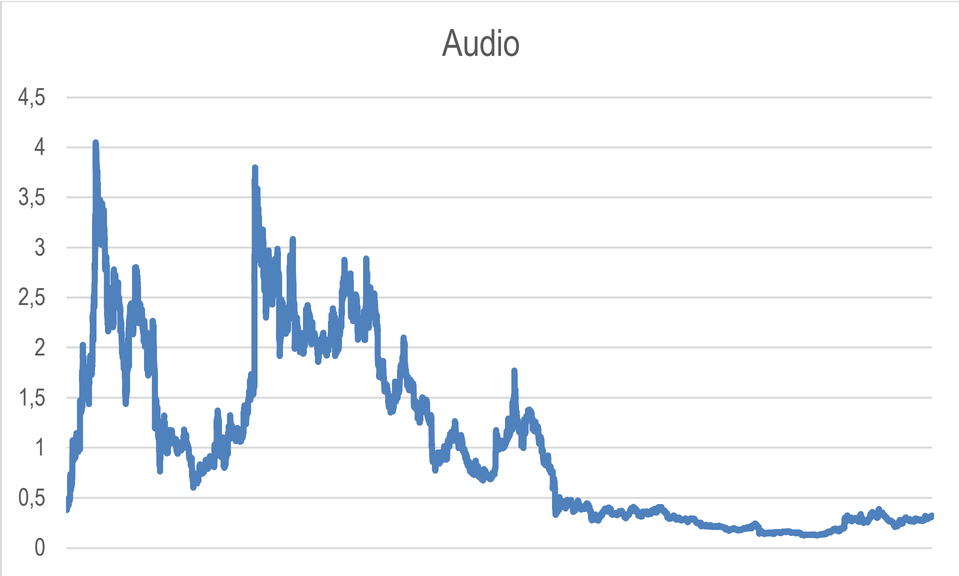

Table 42, Audio value

7 RESULTS COMPARED TO RANDOM BUY AND SELL

The previous chapter showed that technical analysis cannot be used for profitable trading in every situation. In this chapter, technical analysis is compared to random investing decisions. This chapter analyses more about how technical analysis performs than the previous chapter, but the previous chapter analyses can technical analysis be used to make a profit. The same methods with the same settings were used for technical analysis.

7.1 Random buy and sell results

Results are calculated in a way that a program randomly buys, sells or does not do either for each line of the CSV-file. That was done 10000 times for every currency for better results. Finally, the median result was calculated and compared on the results of technical analysis.

Aave	-79144
ARPA	129
Audius	-84888
CAKE	-68802
Celo	-81060
decred	-46155
HBAR	-1802
Hive	-49737
ICON	-79590
IOTA	-74303
Jasmine	-3585
Litentry	-93020
Monero	-27359
New Kind of Network	-850
Paris Saint-Germain Fan Token	-63084
Smooth Love Potion	-4130
Stellar Lumens	-3328
Synthetix	-88200
Uniswap	-80525
Wave	-79559
Yield Guild Games	-91194
Zcash	-70838

Table 43 shows the result of 10000 runs of random buy and sell

The results of randomness vary very much between the currencies. It varies because of the market situation when the research was done. These results are the average of 10000 runs of randomness, and some currencies have been double-checked. Random investing is not recommended because traders sometimes lose almost everything, as seen in Table 43.

7.2 Overall performance

	average	median	max	min
TA	-44301,36	-55776,20	100422,14	-97155,60
TA-fee	-44898,71	-56048,16	99861,71	-97292,69
Rdm	-52014,68	-69633,75	2409,29	-92027,41
Rdm-fee	-53228,46	-69820,20	128,94	-93020,37
Diff.	7713,32	13857,55	98012,85	-5128,19
Diff. -fee	8329,76	13772,04	99732,77	-4272,32

Table 44, Technical analysis compared to randomness

Technical analysis does make a difference. The extra eight percentage points of profit is enormous compared to the average stock market profit. The median result is even more significant: 14 percentage points. The minimum result was the opposite.

In this research amount of trades was significantly reduced. For faster research, Binances CSV files were cut and only one trade per hour was left on the CSV file. Therefore, the number of trades was significantly smaller than it would have been if all the data had been used and the total fee amount was less. With this amount of trade, the amount of fees is also reasonable.

7.2.1 Technical analysis methods

			Compared to Random
Bollinger	Average	-45039,74	8188,72

	Median	-61900,73	7919,47
	Max	99861,71	99732,77
	Min	-95521,3	-2500,93
EMA	Average	-43888,84	9339,62
	Median	-48520,48	21299,72
	Max	72340,53	72211,59
	Min	-97292,69	-4272,32
Macd	Average	-50820,78	2407,68
	Median	-54533,82	15286,38
	Max	15337	15208,06
	Min	-87555,09	5465,28
RSI	Average	-29448,77	23779,69
	Median	-40669,7	29150,50
	Max	44398,95	44270,01
	Min	-90105,99	2914,38
SMA	Average	-42774,79	10453,67
	Median	-43457,39	26362,81
	Max	37960,05	37831,11
	Min	-92619,17	401,20

Table 45, Different methods compared to random

Every method of technical analysis is better than randomness. Only Minimum results are sometimes worse with some technical analysis methods.

7.2.2 Bollinger bands

Period	STD	Type	average	median	max	min
20	2	0	7021,68	7835,76	84270,24	-2500,93
20	2	1	6912,85	7821,75	86505,55	-2500,93
20	2	2	7246,74	7940,46	87234,91	-2500,93
20	2,5	0	8359,75	7890,53	87238,65	-2500,93
20	2,5	1	7942,12	7926,12	88081,36	-2500,93

20	2,5	2	8097,72	7984,30	88741,62	-2500,93
20	3	0	9234,15	7704,03	93246,35	-2500,93
20	3	1	8915,89	7877,65	89521,75	-2500,93
20	3	2	8968,06	7873,11	90480,04	-2500,93
21	2	0	7150,02	7936,86	84923,75	-2500,21
21	2	1	7003,26	8071,98	86797,50	-2500,21
21	2	2	7310,43	7899,72	86815,66	-2500,21
21	2,5	0	8408,83	8022,56	87777,99	-2500,21
21	2,5	1	8056,59	7951,51	88665,71	-2500,21
21	2,5	2	8180,55	7988,88	88634,91	-2500,21
21	3	0	9468,68	7716,83	96735,03	-2500,21
21	3	1	8925,68	7812,90	87854,36	-2500,21
21	3	2	9090,06	7873,33	90971,06	-2500,21
22	2	0	7219,07	8062,90	85455,49	-2494,93
22	2	1	7043,51	8188,59	86419,65	-2494,93
22	2	2	7407,65	8135,03	87521,95	-2494,93
22	2,5	0	8633,46	8022,76	88272,28	-2494,93
22	2,5	1	8162,79	7940,90	88542,12	-2494,93
22	2,5	2	8236,50	8002,40	88662,12	-2494,93
22	3	0	9740,59	7707,63	99732,77	-2494,93
22	3	1	9067,96	7798,00	88012,46	-2494,93
22	3	2	9290,83	7861,72	91689,54	-2494,93

Table 46, Bollinger bands on different settings compared to randomness

Bollinger Bands performed better than randomness. The differences were almost same with every setting. Average performance was 7 - 9 percentage points better, and median performance was eight percentage points better than randomness.

7.2.3 EMA

Period	Average	Median	Max	Min
5	10781,89	22172,36	72340,53	-2627,29
10	12050,03	23721,79	72340,53	-992,68
20	11118,34	23380,84	72340,53	-1266,80
50	7393,94	12875,77	72340,53	-2938,84
100	6974,01	20560,41	72340,53	-4272,32
200	7719,51	19914,00	72340,53	-2555,77

Table 47, EMA settings compared to randomness

On EMA, there were more spread results. Average results were 7 – 12 percentage points better with technical analysis, and median results were 13 – 23 percentage points better.

7.2.4 MACD

fast	slow	signal	average	median	max	min
5	35	5	1607,28	15805,36	-8539,39	8868,79
6	13	5	4401,56	21800,88	-10258,07	12000,05
7	14	7	-837,47	13832,95	-19816,54	7038,58
8	17	9	-2378,50	10062,09	-14537,07	5625,05
10	20	5	-1415,09	10534,55	-11356,48	5465,28
10	30	5	143,50	16706,46	-5222,96	8894,95
12	26	9	-13,83	17117,61	-20251,17	11084,23
15	30	5	1806,71	16616,81	-15228,50	10717,79
18	35	6	7275,63	18536,13	15208,06	10090,05
21	55	8	13486,98	26869,33	5094,20	8952,86

Table 48, MACD settings compared to randomness

MACD differs from previous methods in the way that, in some cases, average performance was worse than the performance of randomness. The reason for that might be the market situation, but it is not clear what the reason is. The problem with this research is that only one market situation is researched and situation could differ on different market situation.

7.2.5 RSI

Period	Average	Median	Max	Min
7	14078,47	25017,27	28827,69	2914,38
14	21655,37	32469,34	28827,69	6577,10
21	35605,23	52465,62	28827,69	15441,99

Table 49, RSI settings compared to randomness

RSI was unprofitably in this market situation, but performed much better than randomness. Median performance was 25 - 52 percentage points better.

7.2.6 SMA

		average	median	max	min
10	20	6257,74	17798,17	16633,67	2937,49
10	50	12913,47	24870,36	14820,41	5453,08
20	50	14964,11	26781,46	30824,07	7175,93
50	100	17598,64	32228,06	37831,11	4595,96
50	200	534,38	8593,33	21750,96	401,20

Table 50, SMA settings compared to randomness

SMA had a big median difference in randomness, but the average performance on setting 50,200 was only a little better than randomness. Average performance is important if the trader trades multiple currencies simultaneously. Median performance is much more critical if the trader trades only one currency at a time.

7.2.7 Conclusion of technical analysis methods performance

Compared to random buying and selling, every technical analysis method performed better. Only a couple of settings performed worse. Based on the situation market had at the moment when this research was done, RSI is the best tool for the help of investing. It performed much better than randomness. EMA and SMA also performed well, but the variance on SMA was much higher than on EMA. With SMA, there is a need to choose the best settings carefully. In worst settings, SMA is only a little bit better than randomness.

7.2.8 Cryptocurrencies on Payments-category

	Average	Median	Max	Min
All	-19974,39	-24846,54	-4184,90	-3007,52
Bollinger	-24937,94	-24966,28	-57763,90	7613,34
EMA	-12076,07	-14425,64	-17861,88	1976,32
Macd	-28150,81	-28368,72	-42168,96	-3007,52
RSI	3355,41	1075,29	-4184,90	2795,67
SMA	-294,25	-604,19	-11405,08	16326,02

Table 51, Different technical analysis compared to randomness on payments-category

The payments category had two currencies: Celo and XLM. Randomness performed exceptionally well on XML. Profit was -3328. The value of XLM was more steady than Celo's, which most likely explains why randomness performed better on XLM. XLM randomness performance is the reason why technical analysis methods performed badly compared to randomness. RSI performance was better on technical analysis than randomness.

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7.2.9 Cryptocurrencies on Smart Contracts-category

	Average	Median	Max	Min
All	35176,44	52674,24	99732,77	-15122,83
Bollinger	53213,07	62508,80	99732,77	-1949,39
EMA	18224,23	32144,31	67011,60	-15122,83
Macd	8802,59	22171,54	15208,06	11727,29
RSI	34384,51	49587,63	30677,29	-4902,47
SMA	11344,15	26813,51	37831,11	-7899,58

Table 52, Different technical analysis compared to randomness on performance on category

The intelligent contracts category has four currencies: Uniswap, Waves, Decred and ARPA chain. In this category, technical analyses performed better than randomness in every method. The median difference was 22 – 63 percentage points. However, the average performance was only 9 – 53 percentage points better. Still, even in the worst-case scenario, it would be a good idea to use technical analysis on the smart contract category instead of randomly buying and selling.

7.2.10 Cryptocurrencies on Privacy-category

	Average	Median	Max	Min
All	38304,74	45246,45	87296,49	20983,17
Bollinger	44825,01	44512,75	49568,21	40144,01
EMA	43247,34	42653,95	87296,49	21069,33
Macd	20654,04	20011,80	22265,39	20983,17
RSI	42713,29	43147,47	59073,63	28078,74
SMA	29820,48	25570,82	33040,80	35400,41

Table 53, Different technical analysis compared to randomness on Privacy category

The privacy category had two currencies: Monero and Zcash. Only two currencies were researched in this category, which might explain the relatively steady results between average and median results. There are two groups: the ones that performed more than 40 percentage points better than randomness and those that performed only 20 percentage points better than randomness. Based on this result, technical analysis works very well in the privacy category.

7.2.11 Cryptocurrencies on random coins-category

	Average	Median	Max	Min
All	28184,07	16824,70	135424,56	16362,69
Bollinger	14483,13	16151,84	11132,88	16482,12
EMA	47549,28	43715,66	135424,56	26770,83
Macd	35914,78	36287,04	68307,17	22146,64
RSI	72988,39	81048,77	107482,98	41342,81
SMA	36586,83	35823,82	65304,96	16362,69

Table 54, Different technical analysis compared to randomness on random coins category

The random coins category had four currencies: Paris Saint-German Fan token, Litentry, Synthetix and Aave. RSI performed exceptionally well. Median difference were 80 percentage points better than randomness, and an average difference were 73 percentage points better. Bollinger's band did not perform as well as others, but it performed better than randomness. Technical analysis methods performed approximately 35 – 40 percentage points better than randomness. Based on that, technical analysis does work in this category.

7.2.12 Cryptocurrencies on Decentralised Finance (DeFi) -category

	Average	Median	Max	Min
All	-1129,73	-14952,08	55371,44	-15380,43
Bollinger	-15240,61	-15318,30	-14903,64	-15380,43
EMA	-1131,65	-722,53	4851,92	-8432,58
Macd	13476,02	12710,44	23724,91	6744,95
RSI	24346,43	24590,30	34709,80	13739,20

SMA	30574,14	25662,06	55371,44	12497,08

table 55, Different technical analysis compared to randomness on Decentralised Finance category

In the Decentralised Finance category, there was only Cake currency researched. The cake did not perform well on randomness. The result was -68802. Randomness performed better than Bollinger and EMA. That result cannot be explained by the fact that randomness would have worked great. It is hard to see why Bollinger and EMA performed worse than randomness. Cake's value changes seemed pretty much the same as other currencies value changes. At the beginning of the timeline, the value rose to 4 times the value at the beginning and then dropped to half the value of the beginning. SMA, RSI and Macd performed well on Cake.

7.2.13 Cryptocurrencies on Gaming-category

	Average	Median	Max	Min
All	-35727,26	-43815,19	-18533,72	-6099,00
Bollinger	-43826,05	-43827,19	-83308,79	-4327,61
EMA	-38086,32	-37743,04	-67835,55	-6099,00
Macd	-21877,86	-22251,79	-48848,66	3638,60
RSI	-18454,31	-23754,72	-18533,72	1087,70
SMA	-27225,43	-24808,45	-43917,95	-1425,48

Table 56, Different technical analysis compared to randomness in the Gaming category

The gaming category had two currencies: Yield Guild Games and Smooth Love Potion. Technical analysis performance was terrible compared to randomness. On the closer examination it was because result of randomness on SLP was -4129, while typical technical analysis results were -70000. With SML, there were massive changes in the value at the beginning of the timeline and after the beginning value dropped slowly. The poor result of the technical analysis can be explained by the excellent result of the randomness of one currency in the researched category.

7.2.14 Cryptocurrencies on Cross-Border Payments-category

	Average	Median	Max	Min
All	-6072,12	-5393,56	18665,58	-4850,88
Bollinger	-4771,83	-4975,83	-38643,44	28346,66
EMA	3050,42	4023,17	-16399,25	15378,32
Macd	-15956,86	-16665,70	-24308,59	9791,66
RSI	5125,24	5972,23	18665,58	8573,76
SMA	-10989,73	-5839,20	-37177,13	-4850,88

Table 57, Different technical analysis compared to randomness on Cross-Border Payments category

In the Cross-Border Payments category, there were ICON and New Kind of Network currencies. NKN performed great with randomness, which affects the way that technical analysis performed very poorly compared to randomness. NKN had an average result of -850 on randomness on 10000 random buy and sell runs. NKN rose from 0.04 to 1.4 at the beginning, explaining why randomness performed well. However, the rise was relatively fast, so technical analysis might not be fast enough to notice the rise fast enough.

7.2.15 Cryptocurrencies on Energy Efficiency-category

	Average	Median	Max	Min
All	-63145,11	-63076,62	-40149,22	-79615,01
Bollinger	-63236,45	-63076,62	-62298,87	-64953,73
EMA	-57472,52	-57821,64	-41595,90	-70008,13
Macd	-66907,34	-69913,57	-40149,22	-79615,01
RSI	-71843,38	-72348,91	-67404,81	-75776,43
SMA	-56715,54	-53011,79	-50190,54	-69132,01

Table 58, Different technical analysis compared to randomness on Energy efficiency category

In the energy efficiency category, only one currency was researched: HBAR. Randomness performed well. The result was -1801. Randomness performance might be that good because the price average was relatively steady. However, none of the technical analysis methods did perform well. All of the results were negative. There is a need for research with a much more enormous scope for knowing why technical analysis performed as poorly as it did. There is no clear reason for this kind of result for the scope of this research.

7.2.16 Cryptocurrencies on Internet of Things (IoT) -category

	Average	Median	Max	Min
All	12599,12	12110,86	34305,03	-6241,30
Bollinger	12035,61	12110,86	12297,84	11508,17
EMA	21731,58	22127,79	27571,72	14662,43
Macd	6506,17	4130,36	24966,04	379,96
RSI	18659,49	21088,76	21503,89	13385,82
SMA	13232,77	11071,44	34305,03	-6241,30

Table 59, Different technical analysis compared to randomness on Internet of Things category

In the Internet of Things category, only IOTA was researched. Researched currency performed poorly on randomness. That might be why technical analysis performed much better than randomness. Still, the technical analysis methods did not perform much better: Macd, for example, performed only slightly better. On the other hand, EMA and RSI performed much better.

7.2.17 Cryptocurrencies in Social Media-category

	Average	Median	Max	Min
All	9475,47	16100,66	37999,79	2064,39
Bollinger	11076,75	16100,66	-10750,10	27158,73
EMA	-4340,14	-7965,60	5077,83	7627,82
Macd	3895,88	10360,61	-290,33	9199,90
RSI	19006,62	2380,94	37999,79	20717,01
SMA	22847,81	63002,42	34538,11	2064,39

Table 60, Different technical analysis compared to randomness on Social media category

Three currencies were researched in the Social media category: Jasmine, Hive and Audius. As seen earlier in this research, technical analysis performed exceptionally well in this category. As a result, it was unprofitable but much less unprofitably than on the many other categories. Technical analysis performed better than randomness, not much, except median SMA, which performed much better. Median SMA was even profitable. Jasmine performed great on randomness. The result was -3585. Hive was -49737, but Audius was -84887. In this category, the average and median had enormous differences. On RSI, average performance was much better than median performance, and on SMA, median performance was much better than average performance.

7.2.18 Conclusion of methods performance in different categories

Based on this research, it cannot be said if there are significant differences between the performance of technical analysis on different categories. The performance of randomness explains most differences between performances. Also, just one to four currencies per category are not enough to make a difference. Therefore, the result does not represents trustfully the whole category. Categories are not clear enough to make a difference. Most of the currencies could also be in another category. On cryptocurrencies, there are currencies which present better the selected categories. However, the popularity of those currencies is too high, and therefore trade files were too big to research on the scope of this research.

8 DISCUSSION AND CONCLUSION

8.1 Summary of findings

Cryptocurrencies are an excellent platform for testing out technical analysis. Buying and selling cryptocurrencies is not limited to the opening times of stock markets. It is possible to trade cryptocurrencies any time of the day and any time of the year. Much free data about past trades is needed for calculating different technical analysis methods. Using different technical analysis methods is relatively easy for anyone who knows the basic of the Python programming language. There is Ta-lib which can be imported into Python code. At the basic, Python can only use one core for calculating. Nowadays, processors have multiple cores, and there are two ways to use the full potential of the central processing unit. One way is to make Python code use multicores. If the user has only basic information about Python, running different code as often as there are cores on the CPU is much easier. If the list of trades is long, it might take half an hour to 12 hours to complete the calculation using one method on one cryptocurrency. The nature of the data and calculations does not benefit from using GPU on calculations. Calculations do not need any special equipment. A typical CPU is good enough, but the amount of data needs more special equipment. In this research, there was a point that 128 GB of memory was not enough. The need for memory was solved by researching only smaller cryptocurrencies which did not have that many trades on the selected timeline. For example, Bitcoin would have 80GB of data on a selected timeline, while researched currencies only had a maximum of 3 GB of trading data. Need for memory growth a lot when researching multiple currencies at the same time to make use of all the cores. That did make the calculation process a lot faster, but at the same time, it also increased the need for memory.

Technical analysis methods do help to make better decisions when investing in cryptocurrencies. However, technical analysis is not a perfect or easy way to make money. Without knowledge about technical analysis methods or cryptocurrencies, trade profit depends more on luck than the tools. Methods do predict the change in the price. Still, in the tested settings and market situation, the value changes were insignificant, and the fee Binance takes from every trade was too much. Because of fees, profitable trading did change to unprofitably. The fee is a small amount, but it goes on every trade. It does not matter if the trade is profitable or unprofitable, and it does not matter if the trader is selling or buying. The trade fee goes in every situation. When a trading

amount is $1000, the fee is $0.75. That is not much, but it is $0.15 when the trader buys and sells. Even a small fee significantly affects results when there are many trades.
Bitcoin decreased at the end of the year (coin club, 2022), and as seen in this research, most of the coins researched went down. Christmas was approximately at half of the timeline. However, the price stayed down for the rest of the timeline. The reason for that is unknown.
There are many reasons why the value of cryptocurrencies has changed. In some cases, technical analysis methods can predict price movement, but the technical analysis does not give enough information for good investment decisions. That is because investors cannot know if the technical analysis is right or wrong until the price changes.
Typically, technical analysis helps traders make better decisions and is more profitable (or less unprofitable) than random investing. However, technical analysis does not necessarily make a profit in a market situation where all the currencies values are going down. On the contrary, it might make even huge losses.

8.2 Discussion

For future research, there would be a need to research more popular currencies that were not researched because of the size of the currencies trading files. A bigger trading file means many calculations cannot be run simultaneously because every calculation takes the whole data to the memory. One way to solve the problem would be to make a code which loads the file to the memory only once, not once per tested method. Another possibility would be using a computer with more memory than the one used in this research. Initially, the computer used in this research had only 128GB of memory, but it was increased to 160 GB. Still, that amount would allow only two Bitcoin calculations simultaneously. That is still not much because this research tested 50 technical analysis methods on one currency. It should be possible to load Bitcoin data only once to the memory, and every running process would read the same data, but that again would need more advanced programming.
In this research, only basic settings were tested. Running the same data with more settings would reveal the best possible settings for every method. Another way to find better working settings would be to use multiple methods together before deciding on buying and selling.

For better knowledge about different categories, there is a need to research more currencies from every category. It is essential to have multiple currencies, especially when comparing technical analysis methods for the random trading strategy. There is a too big change for randomness if not enough currencies are tested. If tested with one or two currencies, they might perform great or poorly just by accident.

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APPENDIX

Appendix 1, Currencies in their category

		Average of All	payments	smart cont	privacy	random	DeFi	Gaming	Cross-bord	Energy	IoT	Social med
All	Average	-50485,11	-62168,60	-16351,21	-10794,00	-52677,92	-69932,06	-83388,96	-46292,45	-64947,06	-61704,29	-36594,54
	Median	-52947,59	-67040,75	-10183,11	-3852,29	-66847,07	-83754,41	-91476,89	-45613,89	-64878,57	-62192,55	-33636,37
	Max	15881,21	-7513,32	99861,71	59937,08	72340,53	-13430,89	-22663,42	17815,24	-41951,17	-39998,38	34414,69
	Min	-81692,96	-84067,51	-95647,66	-49854,90	-76657,68	-84182,76	-97292,69	-84441,20	-81416,96	-80544,71	-82823,50
Bollinger	Average	-51892,16	-67132,15	1685,42	-4273,73	-66378,86	-84042,94	-91487,75	-44992,16	-65038,40	-62267,80	-34993,26
	Median	-52112,81	-67160,49	-348,55	-4585,99	-67519,93	-84120,63	-91488,89	-45196,16	-64878,57	-62192,55	-33636,37
	Max	-34205,28	-61092,32	99861,71	22208,80	-51951,15	-83705,97	-87438,49	-39493,78	-64100,82	-62005,57	-14335,20
	Min	-68138,10	-73446,65	-82474,22	-30694,06	-76538,25	-84182,76	-95521,30	-51243,66	-66755,68	-62795,24	-57729,16
EMA	Average	-48184,62	-54270,28	-33303,42	-5851,40	-33312,71	-69933,98	-85748,02	-37169,91	-59274,47	-52571,83	-50410,15
	Median	-49436,24	-56619,85	-30713,04	-6444,79	-39956,11	-69524,86	-85404,74	-36197,16	-59623,59	-52175,62	-57702,63
	Max	-6357,42	-21190,30	67140,54	59937,08	72340,53	-63950,41	-71965,25	-17249,59	-43397,85	-46731,69	1492,73
	Min	-73820,03	-79083,67	-95647,66	-49768,74	-66249,54	-77234,91	-97292,69	-64212,00	-71810,08	-59640,98	-77260,07
Macd	Average	-54618,57	-70345,02	-42725,06	-28444,70	-44947,21	-55326,31	-69539,56	-56177,19	-68709,29	-67797,24	-42174,13
	Median	-55187,68	-70562,93	-40685,81	-29086,94	-47384,73	-56091,89	-69913,49	-56886,03	-71715,52	-70173,05	-39376,42
	Max	-24840,99	-45497,38	15337,00	-5094,02	5223,14	-45077,42	-52978,36	-25158,93	-41951,17	-49337,37	-3875,43
	Min	-72403,32	-84067,51	-68797,54	-49854,90	-70873,73	-62057,38	-87555,09	-69798,66	-81416,96	-73923,45	-75687,99
RSI	Average	-37226,06	-38838,80	-17143,14	-6385,45	-7873,60	-44455,90	-66116,01	-35095,09	-73645,33	-55643,92	-27063,39
	Median	-38756,11	-41118,92	-13269,72	-5951,27	-2623,00	-44212,03	-71416,42	-34248,10	-74150,86	-53214,65	-47356,09
	Max	-2712,62	-7513,32	30806,23	31714,22	44398,95	-34092,53	-22663,42	17815,24	-69206,76	-52799,52	34414,69
	Min	-67698,10	-78264,32	-85427,30	-42759,33	-51677,56	-55063,13	-90105,99	-71016,56	-77578,38	-60917,59	-64170,88

SMA	Average	-45336,11	-42488,46	-40183,50	-19278,26	-44275,16	-38228,19	-74887,13	-51210,06	-58517,49	-61070,64	-23222,20
	Median	-41666,84	-42798,40	-36043,84	-23527,92	-47847,95	-43140,27	-72470,15	-46059,53	-54813,74	-63231,97	13265,39
	Max	-12941,50	-14733,50	37960,05	5681,39	2220,93	-13430,89	-48047,65	-38027,47	-51992,49	-39998,38	30953,01
	Min	-73292,15	-64733,97	-88424,41	-35437,66	-76657,68	-56305,25	-92619,17	-84441,20	-70933,96	-80544,71	-82823,50

Appendix 2, Currencies Compared to Others

		payments	smart cont	privacy	random	DeFi	Gaming	Cross-bord	Energy	IoT	Social med
All	Average	-11683,49	34133,90	39691,11	-2192,81	-19446,95	-32903,85	4192,65	-14461,95	-11219,18	13890,57
	Median	-14093,16	42764,48	49095,30	-13899,47	-30806,82	-38529,30	7333,70	-11930,98	-9244,96	19311,23
	Max	-23394,52	83980,50	44055,87	56459,32	-29312,10	-38544,63	1934,03	-57832,38	-55879,58	18533,48
	Min	-2374,55	-13954,71	31838,06	5035,28	-2489,80	-15599,73	-2748,24	275,99	1148,25	-1130,54
Bollinger	Average	-15239,99	53577,58	47618,43	-14486,69	-32150,78	-39595,59	6900,01	-13146,23	-10375,64	16898,90
	Median	-15047,68	51764,26	47526,82	-15407,11	-32007,82	-39376,08	6916,66	-12765,76	-10079,74	18476,45
	Max	-26887,04	134066,98	56414,08	-17745,87	-49500,70	-53233,21	-5288,50	-29895,54	-27800,29	19870,08
	Min	-5308,55	-14336,12	37444,04	-8400,15	-16044,66	-27383,20	16894,44	1382,42	5342,86	10408,94
EMA	Average	-6085,66	14881,20	42333,21	14871,91	-21749,37	-37563,40	11014,71	-11089,85	-4387,21	-2225,54
	Median	-7183,61	18723,20	42991,45	9480,13	-20088,62	-35968,50	13239,08	-10187,35	-2739,38	-8266,39
	Max	-14832,88	73497,97	66294,50	78697,95	-57592,99	-65607,83	-10892,17	-37040,43	-40374,27	7850,15
	Min	-5263,63	-21827,63	24051,29	7570,49	-3414,88	-23472,65	9608,04	2009,95	14179,05	-3440,03
Macd	Average	-15726,45	11893,51	26173,87	9671,36	-707,74	-14920,99	-1558,62	-14090,72	-13178,67	12444,44
	Median	-15375,25	14501,87	26100,74	7802,95	-904,20	-14725,81	-1698,35	-16527,84	-14985,37	15811,26
	Max	-20656,39	40177,99	19746,98	30064,13	-20236,43	-28137,36	-317,93	-17110,18	-24496,38	20965,56
	Min	-11664,19	3605,78	22548,42	1529,59	10345,95	-15151,77	2604,66	-9013,64	-1520,13	-3284,67
RSI	Average	-1612,74	20082,93	30840,62	29352,46	-7229,84	-28889,95	2130,97	-36419,27	-18417,86	10162,68
	Median	-2362,81	25486,39	32804,84	36133,10	-5455,92	-32660,31	4508,00	-35394,76	-14458,54	-8599,99
	Max	-4800,69	33518,86	34426,84	47111,57	-31379,91	-19950,80	20527,86	-66494,13	-50086,90	37127,31
	Min	-10566,21	-17729,20	24938,78	16020,55	12634,97	-22407,89	-3318,45	-9880,28	6780,52	3527,23
SMA	Average	2847,65	5152,61	26057,85	1060,95	7107,92	-29551,02	-5873,95	-13181,38	-15734,53	22113,91
	Median	-1131,56	5623,00	18138,92	-6181,11	-1473,43	-30803,32	-4392,70	-13146,90	-21565,13	54932,23
	Max	-1792,00	50901,55	18622,89	15162,43	-489,39	-35106,15	-25085,97	-39050,99	-27056,88	43894,52
	Min	8558,18	-15132,26	37854,49	-3365,53	16986,90	-19327,02	-11149,05	2358,19	-7252,56	-9531,35

Appendix 3, code used for calculating SMA

```
import sys
import os
import csv
import pandas as pd
import numpy as np
import talib
from datetime import datetime, timedelta
import argparse


def read_data(filename):
    data = pd.read_csv(filename, header=None, names=['id', 'Price', 'quantity', 'value', 'Timestamp', 'maker', 'match'])
    data['Date'] = pd.to_datetime(data['Timestamp'], unit='ms')
    return data

def calculate_sma(price_data, period, moving_avg_type=0):
    if moving_avg_type == 0:
        return talib.SMA(price_data, timeperiod=period)
    elif moving_avg_type == 1:
        return talib.EMA(price_data, timeperiod=period)
    elif moving_avg_type == 2:
        return talib.WMA(price_data, timeperiod=period)
    elif moving_avg_type == 3:
        return talib.SMA(price_data, timeperiod=period)

def trade(smas, data, starting_money, start_index):
    money = starting_money
    crypto = 0
    trades = []
    max_transaction = 1000
    last_trade_time = data.loc[start_index, 'Date'].to_pydatetime()
    cooldown_period = pd.Timedelta(minutes=1)
    trade_fee = 0.0
#   trade_fee = 0.00075
    sma_length = min(len(smas[0][~np.isnan(smas[0])]), len(smas[1][~np.isnan(smas[1])]))

    # Add this line to limit the loop to the length of the data
    sma_length = min(sma_length, len(data) - start_index)

    for i in range(start_index, start_index + sma_length):
        current_time = data.loc[i, 'Date'].to_pydatetime()
```

```
        # Check if SMA values are calculated for the current index
        if all(sma[i - start_index] is not None for sma in smas):
            # Implement your own trading strategy using the SMA values in 'smas'
            # Example: Buy when the first SMA crosses above the second SMA
            if smas[0][i - start_index] > smas[1][i - start_index] and money > 0 and current_time - last_trade_time >= cooldown_period:
                buy_amount = min(max_transaction, money)
                buy_amount_after_fee = buy_amount * (1 - trade_fee)
                crypto += buy_amount_after_fee / data.loc[i, 'Price']
                money -= buy_amount
                trades.append(('buy', i))
                last_trade_time = current_time
            # Example: Sell when the first SMA crosses below the second SMA
            elif smas[0][i - start_index] < smas[1][i - start_index] and crypto > 0 and current_time - last_trade_time >= cooldown_period:
                sell_amount = min(max_transaction, crypto * data.loc[i, 'Price'])
                sell_amount_after_fee = sell_amount * (1 - trade_fee)
                crypto_to_sell = sell_amount_after_fee / data.loc[i, 'Price']
                money += sell_amount_after_fee
                crypto -= crypto_to_sell
                trades.append(('sell', i))
                last_trade_time = current_time
    return trades, money, crypto

def trade_sma(price_data, sma_settings, data, starting_money, start_index):
    smas = [calculate_sma(price_data, setting[0], setting[1]) for setting in sma_settings]
    return trade(smas, data, starting_money, start_index)


def save_results(filename, sma_settings, trades, price_data, money, crypto, starting_money):
    profitable_trades = 0
    unprofitable_trades = 0
    for i in range(len(trades) - 1):
        if trades[i][0] == 'buy' and trades[i + 1][0] == 'sell':
            if price_data[trades[i + 1][1]] > price_data[trades[i][1]]:
                profitable_trades += 1
            else:
                unprofitable_trades += 1

    total_money = money + crypto * price_data[-1]
    profit = total_money - starting_money

    # Save results
    output_dir = f'{filename}_results'
    os.makedirs(output_dir, exist_ok=True)
```

```
    output_file = os.path.join(output_dir, f'SMA_{sma_settings}.txt')

    with open(output_file, 'w') as f:
        f.write(f'SMA settings: {sma_settings}\n')
        f.write(f'Profitable trades: {profitable_trades}\n')
        f.write(f'Unprofitable trades: {unprofitable_trades}\n')
        f.write(f'Total trades: {profitable_trades + unprofitable_trades}\n')
        f.write(f'End money: {money}\n')
        f.write(f'Value of cryptocurrencies: {crypto * price_data[-1]}\n')
        f.write(f'Total money (end money + value of cryptocurrencies): {total_money}\n')
        f.write(f'Profit or loss: {profit}\n')


def main(filename, sma_settings):
    data = read_data(filename)
    price_data = data['Price'].values
    timestamps = data['Timestamp'].values
    starting_money = 100000

    start_time = data.loc[0, 'Date'] + timedelta(days=200)
    start_index = np.argmax(data['Date'].values >= np.datetime64(start_time))

    # Ensure the start_index is within the bounds of the data
    if start_index >= len(data):
        print("Start index is out of range. Please adjust the start_time or input more data.")
        return

    trades, money, crypto = trade_sma(price_data, sma_settings, data, starting_money, start_index)

    save_results(filename, sma_settings, trades, price_data, money, crypto, starting_money)

if __name__ == "__main__":
    parser = argparse.ArgumentParser(description='Crypto trading using TA-Lib and SMA.')
    parser.add_argument('filename', type=str, help='CSV file with price data')
#    parser.add_argument('--sma_settings', nargs='+', type=int, help='SMA settings as a list of integers: period_1 moving_avg_type_1 period_2 moving_avg_type_2 ...')
    parser.add_argument('--sma_settings', nargs='+', type=int, help='SMA settings as a list of integers: period_1 moving_avg_type_1 period_2 moving_avg_type_2')

    args = parser.parse_args()

    # Group the sma_settings into a list of tuples
    sma_settings = [(args.sma_settings[i], args.sma_settings[i+1]) for i in range(0, len(args.sma_settings), 2)]

    main(args.filename, sma_settings)
```

Appendix 4, code used for calculating RSI

```
import sys
import os
import csv
import pandas as pd
import numpy as np
import talib
from datetime import datetime, timedelta
import argparse


def read_data(filename):
    data = pd.read_csv(filename, header=None, names=['id', 'Price', 'quantity', 'value', 'Timestamp', 'maker', 'match'])
    data['Date'] = pd.to_datetime(data['Timestamp'], unit='ms')
    return data


def calculate_rsi(price_data, rsi_period):
    rsi = talib.RSI(price_data, timeperiod=rsi_period)
    return rsi


def trade(rsi, data, starting_money, start_index, overbought_level, oversold_level):
    money = starting_money
    crypto = 0
    trades = []
    max_transaction = 1000
    last_trade_time = data.loc[start_index, 'Date'].to_pydatetime()
    cooldown_period = pd.Timedelta(minutes=1)
    trade_fee = 0.0
#    trade_fee = 0.00075


    for i in range(start_index, len(data)):
        current_time = data.loc[i, 'Date'].to_pydatetime()
        if rsi[i - start_index] <= oversold_level and money > 0 and current_time - last_trade_time >= cooldown_period:
            buy_amount = min(max_transaction, money)
            buy_amount_after_fee = buy_amount * (1 - trade_fee)
            crypto += buy_amount_after_fee / data.loc[i, 'Price']
            money -= buy_amount
            trades.append(('buy', i))
```

```
            last_trade_time = current_time
        elif rsi[i - start_index] >= overbought_level and crypto > 0 and current_time - last_trade_time >= cooldown_period:
            sell_amount = min(max_transaction, crypto * data.loc[i, 'Price'])
            sell_amount_after_fee = sell_amount * (1 - trade_fee)
            crypto_to_sell = sell_amount_after_fee / data.loc[i, 'Price']
            money += sell_amount_after_fee
            crypto -= crypto_to_sell
            trades.append(('sell', i))
            last_trade_time = current_time
    return trades, money, crypto


def save_results(filename, rsi_period, overbought_level, oversold_level, trades, price_data, money, crypto, starting_money):
    profitable_trades = 0
    unprofitable_trades = 0
    for i in range(len(trades) - 1):
        if trades[i][0] == 'buy' and trades[i + 1][0] == 'sell':
            if price_data[trades[i + 1][1]] > price_data[trades[i][1]]:
                profitable_trades += 1
            else:
                unprofitable_trades += 1

    total_money = money + crypto * price_data[-1]
    profit = total_money - starting_money

# Save results
#def save_results(filename, rsi_period, overbought_level, oversold_level, trades, price_data, money, crypto):
    output_dir = f'{filename}_results'
    os.makedirs(output_dir, exist_ok=True)
    output_file = os.path.join(output_dir, f'RSI_{rsi_period}_overbought_{overbought_level}_oversold_{oversold_level}.txt')

    with open(output_file, 'w') as f:
        f.write(f'RSI period: {rsi_period}\n')
        f.write(f'Overbought level: {overbought_level}\n')
        f.write(f'Oversold level: {oversold_level}\n')
        f.write(f'Profitable trades: {profitable_trades}\n')
        f.write(f'Unprofitable trades: {unprofitable_trades}\n')
        f.write(f'Total trades: {profitable_trades + unprofitable_trades}\n')
        f.write(f'End money: {money}\n')
        f.write(f'Value of cryptocurrencies: {crypto * price_data[-1]}\n')
        f.write(f'Total money (end money + value of cryptocurrencies): {total_money}\n')
        f.write(f'Profit or loss: {profit}\n')

def main(filename, rsi_period, overbought_level, oversold_level):
    data = read_data(filename)
```

```
    price_data = data['Price'].values
    timestamps = data['Timestamp'].values
    starting_money = 100000
    start_time = data.loc[0, 'Date'] + timedelta(days=200)
    start_index = np.argmax(data['Date'].values >= np.datetime64(start_time))

    rsi = calculate_rsi(price_data, rsi_period)
    trades, money, crypto = trade(rsi[start_index:], data, starting_money, start_index, overbought_level, oversold_level)

    save_results(filename, rsi_period, overbought_level, oversold_level, trades, price_data, money, crypto, starting_money)

if __name__ == "__main__":
    parser = argparse.ArgumentParser(description='Crypto trading using TA-Lib and RSI.')
    parser.add_argument('filename', type=str, help='CSV file with price data')
    parser.add_argument('--rsi_period', type=int, default=14, help='RSI period')
    parser.add_argument('--overbought_level', type=int, default=70, help='Overbought level')
    parser.add_argument('--oversold_level', type=int, default=30, help='Oversold level')

    args = parser.parse_args()

    main(args.filename, args.rsi_period, args.overbought_level, args.oversold_level)
```

Appendix 5, code used for calculating macd

```
import sys
import os
import csv
import pandas as pd
import numpy as np
import talib
from datetime import datetime, timedelta
import argparse


def read_data(filename):
    data = pd.read_csv(filename, header=None, names=['id', 'Price', 'quantity', 'value', 'Timestamp', 'maker', 'match'])
    data['Date'] = pd.to_datetime(data['Timestamp'], unit='ms')
    return data

def calculate_macd(price_data, macd_settings):
    macd, signal, _ = talib.MACD(price_data, fastperiod=macd_settings[0], slowperiod=macd_settings[1],
signalperiod=macd_settings[2])
    return macd, signal

def trade(macd, signal, data, starting_money, start_index):
```

```
    money = starting_money
    crypto = 0
    trades = []
    max_transaction = 1000
    last_trade_time = data.loc[start_index, 'Date'].to_pydatetime()
    cooldown_period = pd.Timedelta(minutes=1)
    trade_fee = 0.0
#   trade_fee = 0.00075


    for i in range(start_index, len(data)):
        current_time = data.loc[i, 'Date'].to_pydatetime()
        if macd[i - start_index] > signal[i - start_index] and money > 0 and current_time - last_trade_time >= cooldown_period:
            buy_amount = min(max_transaction, money)
            buy_amount_after_fee = buy_amount * (1 - trade_fee)
            crypto += buy_amount_after_fee / data.loc[i, 'Price']
            money -= buy_amount
            trades.append(('buy', i))
            last_trade_time = current_time
        elif macd[i - start_index] < signal[i - start_index] and crypto > 0 and current_time - last_trade_time >= cooldown_period:
            sell_amount = min(max_transaction, crypto * data.loc[i, 'Price'])
            sell_amount_after_fee = sell_amount * (1 - trade_fee)
            crypto_to_sell = sell_amount_after_fee / data.loc[i, 'Price']
            money += sell_amount_after_fee
            crypto -= crypto_to_sell
            trades.append(('sell', i))
            last_trade_time = current_time
    return trades, money, crypto

def save_results(filename, macd_settings, trades, price_data, money, crypto):
    profitable_trades = 0
    unprofitable_trades = 0
    for i in range(len(trades) - 1):
        if trades[i][0] == 'buy' and trades[i + 1][0] == 'sell':
            if price_data[trades[i + 1][1]] > price_data[trades[i][1]]:
                profitable_trades += 1
            else:
                unprofitable_trades += 1

    total_money = money + crypto * price_data[-1]
    profit = total_money - starting_money

    # Save results
    output_dir = f'{filename}_results'
    os.makedirs(output_dir, exist_ok=True)
```

```
    output_file = os.path.join(output_dir, f'MACD_{macd_settings}.txt')

    with open(output_file, 'w') as f:
        f.write(f'MACD settings: {macd_settings}\n')
        f.write(f'Profitable trades: {profitable_trades}\n')
        f.write(f'Unprofitable trades: {unprofitable_trades}\n')
        f.write(f'Total trades: {profitable_trades + unprofitable_trades}\n')
        f.write(f'End money: {money}\n')
        f.write(f'Value of cryptocurrencies: {crypto * price_data[-1]}\n')
        f.write(f'Total money (end money + value of cryptocurrencies): {total_money}\n')
        f.write(f'Profit or loss: {profit}\n')


def main(filename, macd_settings):
    data = read_data(filename)
    price_data = data['Price'].values
    timestamps = data['Timestamp'].values
    starting_money = 100000

    start_time = data.loc[0, 'Date'] + timedelta(days=200)
    start_index = np.argmax(data['Date'].values >= np.datetime64(start_time))

    macd, signal = calculate_macd(price_data, macd_settings)
    trades, money, crypto = trade(macd[start_index:], signal[start_index:], data, starting_money, start_index)

    profitable_trades = 0
    unprofitable_trades = 0
    for i in range(len(trades) - 1):
        if trades[i][0] == 'buy' and trades[i + 1][0] == 'sell':
            if price_data[trades[i + 1][1]] > price_data[trades[i][1]]:
                profitable_trades += 1
            else:
                unprofitable_trades += 1

    total_money = money + crypto * price_data[-1]
    profit = total_money - starting_money

    # Save results
    output_dir = f'{filename}_results'
    os.makedirs(output_dir, exist_ok=True)
    output_file = os.path.join(output_dir, f'MACD_{macd_settings}.txt')

    with open(output_file, 'w') as f:
        f.write(f'MACD settings: {macd_settings}\n')
        f.write(f'Profitable trades: {profitable_trades}\n')
```

```
        f.write(f'Unprofitable trades: {unprofitable_trades}\n')
        f.write(f'Total trades: {profitable_trades + unprofitable_trades}\n')
        f.write(f'End money: {money}\n')
        f.write(f'Value of cryptocurrencies: {crypto * price_data[-1]}\n')
        f.write(f'Total money (end money + value of cryptocurrencies): {total_money}\n')
        f.write(f'Profit or loss: {profit}\n')

if __name__ == "__main__":
    parser = argparse.ArgumentParser(description='Crypto trading using TA-Lib and MACD.')
    parser.add_argument('filename', type=str, help='CSV file with price data')
    parser.add_argument('--macd_settings', nargs=3, type=int, default=[12, 26, 9], help='MACD settings as a list of three integers: [fastperiod, slowperiod, signalperiod]')

    args = parser.parse_args()

    main(args.filename, args.macd_settings)
```

Appendix 6, code used for calculating ema

```
import sys
import os
import csv
import pandas as pd
import numpy as np
import talib
from datetime import datetime, timedelta
import argparse


def read_data(filename):
    data = pd.read_csv(filename, header=None, names=['id', 'Price', 'quantity', 'value', 'Timestamp', 'maker', 'match'])
    data['Date'] = pd.to_datetime(data['Timestamp'], unit='ms')
    return data


def calculate_ema(price_data, ema_settings):
    ema_values = []
    for period in ema_settings:
        ema_period = int(period)
        ema = talib.EMA(price_data, timeperiod=ema_period)
        ema_values.append(ema)
    return ema_values


def trade(ema_values, data, starting_money, start_index):
```

```
    money = starting_money
    crypto = 0
    trades = []
    max_transaction = 1000
    last_trade_time = data.loc[start_index, 'Date'].to_pydatetime()
    cooldown_period = pd.Timedelta(minutes=1)
    trade_fee = 0.0
#    trade_fee = 0.00075


    for i in range(start_index, len(data)):
        current_time = data.loc[i, 'Date'].to_pydatetime()
        if ema_values[i - start_index] > data.loc[i, 'Price'] and money > 0 and current_time - last_trade_time >= cooldown_period:
            buy_amount = min(max_transaction, money)
            buy_amount_after_fee = buy_amount * (1 - trade_fee)
            crypto += buy_amount_after_fee / data.loc[i, 'Price']
            money -= buy_amount
            trades.append(('buy', i))
            last_trade_time = current_time
        elif ema_values[i - start_index] < data.loc[i, 'Price'] and crypto > 0 and current_time - last_trade_time >= cooldown_period:
            sell_amount = min(max_transaction, crypto * data.loc[i, 'Price'])
            sell_amount_after_fee = sell_amount * (1 - trade_fee)
            crypto_to_sell = sell_amount_after_fee / data.loc[i, 'Price']
            money += sell_amount_after_fee
            crypto -= crypto_to_sell
            trades.append(('sell', i))
            last_trade_time = current_time
    return trades, money, crypto


def save_results(filename, ema_period, trades, price_data, money, crypto, starting_money):
    profitable_trades = 0
    unprofitable_trades = 0
    for i in range(len(trades) - 1):
        if trades[i][0] == 'buy' and trades[i + 1][0] == 'sell':
            if price_data[trades[i + 1][1]] > price_data[trades[i][1]]:
                profitable_trades += 1
            else:
                unprofitable_trades += 1

    total_money = money + crypto * price_data[-1]
    profit = total_money - starting_money

    # Save results
    output_dir = f'{filename}_results'
```

```
    os.makedirs(output_dir, exist_ok=True)
    output_file = os.path.join(output_dir, f'EMA_{ema_period}.txt')

    with open(output_file, 'w') as f:
        f.write(f'EMA period: {ema_period}\n')
        f.write(f'Profitable trades: {profitable_trades}\n')
        f.write(f'Unprofitable trades: {unprofitable_trades}\n')
        f.write(f'Total trades: {profitable_trades + unprofitable_trades}\n')
        f.write(f'End money: {money}\n')
        f.write(f'Value of cryptocurrencies: {crypto * price_data[-1]}\n')
        f.write(f'Total money (end money + value of cryptocurrencies): {total_money}\n')
        f.write(f'Profit or loss: {profit}\n')
def main(filename, ema_settings):
    data = read_data(filename)
    price_data = data['Price'].values
    starting_money = 100000

    start_time = data.loc[0, 'Date'] + timedelta(days=200)
    start_index = np.argmax(data['Date'].values >= np.datetime64(start_time))

    for ema_setting in ema_settings:
        ema_values = calculate_ema(price_data, [ema_setting])
        trades, money, crypto = trade(ema_values[0][start_index:], data, starting_money, start_index)
        save_results(filename, [ema_setting], trades, price_data, money, crypto, starting_money)

if __name__ == "__main__":
    parser = argparse.ArgumentParser(description='Crypto trading using TA-Lib and EMA.')
    parser.add_argument('filename', type=str, help='CSV file with price data')
    parser.add_argument('--ema_settings', nargs='+', type=int, default=[5, 10, 20, 50, 100, 200], help='EMA settings as a list of
integers')

    args = parser.parse_args()

    main(args.filename, args.ema_settings)
```

Appendix 7, code used for calculating Bollinger Bands

```
import sys
import os
import csv
import pandas as pd
import numpy as np
import talib
from datetime import datetime, timedelta
import argparse
```

```
def read_data(filename):
    data = pd.read_csv(filename, header=None, names=['id', 'Price', 'quantity', 'value', 'Timestamp', 'maker', 'match'])
    data['Date'] = pd.to_datetime(data['Timestamp'], unit='ms')
    return data


def calculate_bollinger_bands(price_data, bollinger_settings):
    upper, middle, lower = talib.BBANDS(price_data, timeperiod=bollinger_settings['period'], nbdevup=bollinger_settings['std_dev'],
nbdevdn=bollinger_settings['std_dev'], matype=bollinger_settings['moving_avg_type'])
    return upper, middle, lower


def trade(upper, middle, lower, data, starting_money, start_index, upper_threshold, lower_threshold):
    money = starting_money
    crypto = 0
    trades = []
    max_transaction = 1000
    last_trade_time = data.loc[start_index, 'Date'].to_pydatetime()
    cooldown_period = pd.Timedelta(minutes=1)
    trade_fee = 0.0
#   trade_fee = 0.00075


    for i in range(start_index, len(data)):
        current_time = data.loc[i, 'Date'].to_pydatetime()
        if data.loc[i, 'Price'] <= lower[i - start_index] * (1 + lower_threshold) and money > 0 and current_time - last_trade_time >=
cooldown_period:
            buy_amount = min(max_transaction, money)
            buy_amount_after_fee = buy_amount * (1 - trade_fee)
            crypto += buy_amount_after_fee / data.loc[i, 'Price']
            money -= buy_amount
            trades.append(('buy', i))
            last_trade_time = current_time
        elif data.loc[i, 'Price'] >= upper[i - start_index] * (1 - upper_threshold) and crypto > 0 and current_time - last_trade_time >=
cooldown_period:
            sell_amount = min(max_transaction, crypto * data.loc[i, 'Price'])
            sell_amount_after_fee = sell_amount * (1 - trade_fee)
            crypto_to_sell = sell_amount_after_fee / data.loc[i, 'Price']
            money += sell_amount_after_fee
            crypto -= crypto_to_sell
            trades.append(('sell', i))
            last_trade_time = current_time
    return trades, money, crypto
```

```
def save_results(filename, bollinger_settings, trades, price_data, money, crypto, starting_money):
    profitable_trades = 0
    unprofitable_trades = 0
    for i in range(len(trades) - 1):
        if trades[i][0] == 'buy' and trades[i + 1][0] == 'sell':
            if price_data[trades[i + 1][1]] > price_data[trades[i][1]]:
                profitable_trades += 1
            else:
                unprofitable_trades += 1

    total_money = money + crypto * price_data[-1]
    profit = total_money - starting_money

    output_dir = f'{filename}_results'
    os.makedirs(output_dir, exist_ok=True)
    output_file = os.path.join(output_dir, f'Bollinger_Bands_{bollinger_settings}.txt')

    with open(output_file, 'w') as f:
        f.write(f'Bollinger Bands settings: {bollinger_settings}\n')
        f.write(f'Profitable trades: {profitable_trades}\n')
        f.write(f'Unprofitable trades: {unprofitable_trades}\n')
        f.write(f'Total trades: {profitable_trades + unprofitable_trades}\n')
        f.write(f'End money: {money}\n')
        f.write(f'Value of cryptocurrencies: {crypto * price_data[-1]}\n')
        f.write(f'Total money (end money + value of cryptocurrencies): {total_money}\n')
        f.write(f'Profit or loss: {profit}\n')

def main(filename, bollinger_settings):
    data = read_data(filename)
    price_data = data['Price'].values
    timestamps = data['Timestamp'].values
    starting_money = 100000

    start_time = data.loc[0, 'Date'] + timedelta(days=200)
    start_index = np.argmax(data['Date'].values >= np.datetime64(start_time))

    upper, middle, lower = calculate_bollinger_bands(price_data, bollinger_settings)
    trades, money, crypto = trade(upper, middle, lower, data, starting_money, start_index, bollinger_settings['upper_threshold'],
bollinger_settings['lower_threshold'])

    save_results(filename, bollinger_settings, trades, price_data, money, crypto, starting_money)

if __name__ == "__main__":
```

```
    parser = argparse.ArgumentParser(description='Crypto trading using TA-Lib and Bollinger Bands.')
    parser.add_argument('filename', type=str, help='CSV file with price data')
    parser.add_argument('--period', type=int, default=20, help='Bollinger Bands period')
    parser.add_argument('--std_dev', type=float, default=2, help='Bollinger Bands standard deviation')
    parser.add_argument('--moving_avg_type', type=int, default=0, help='Bollinger Bands moving average type (0 for simple, 1 for
exponential, 2 for weighted, 3 for double exponential)')
    parser.add_argument('--upper_threshold', type=float, default=0.01, help='Bollinger Bands upper threshold')
    parser.add_argument('--lower_threshold', type=float, default=0.01, help='Bollinger Bands lower threshold')

    args = parser.parse_args()

    bollinger_settings = {
        'period': args.period,
        'std_dev': args.std_dev,
        'moving_avg_type': args.moving_avg_type,
        'upper_threshold': args.upper_threshold,
        'lower_threshold': args.lower_threshold
    }

    main(args.filename, bollinger_settings)
```