ISTANBUL TECHNICAL UNIVERSITY
ELECTRICAL-ELECTRONICS FACULTY

PREDICTION OF BITCOIN ENERGY CONSUMPTION THROUGH THE APPLICATION OF THE MACHINE LEARNING

SENIOR DESIGN PROJECT

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ELECTRONICS AND COMMUNICATION ENGINEERING DEPARTMENT

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FOREWORD

First and foremost, I would like to express my deepest gratitude to my family and friends for their unwavering support and endless patience throughout my life. Your encouragement and belief in my potential have been the foundation of everything I have achieved. I am forever grateful for your unconditional love and support.

I would like to thank my advisor, Asst. Prof. Onur Kurt helped me at every stage with his knowledge and experience and ensured that I showed the necessary care and attention to all details.

I also extend my sincere thanks to all the faculty members of the Faculty of Electrical and Electronics Engineering at Istanbul Technical University. You have taught me the fundamental principles of engineering and the ethical dimensions of our profession, which have been crucial in my development as both a student and a future engineer.

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ABBREVIATIONS

AI	**:** Artificial Intelligence
ANN	**:** Artificial Neural Network
ARIMA	**:** Autoregressive Integrated Moving Average
ASIC	**:** Application Specific Integrated Circuit
BPTT	**:** Backpropagation Through Time
CBCEI	**:** The Cambridge Bitcoin Electricity Consumption Index
CSV	**:** Comma Separated Values
FNN	**:** Feedforward Neural Networks
GRU	**:** Gated Recurrent Unit
LSTM	**:** Long Short-Term Memory
MLP	**:** Multi-layer Perceptron
NNAR	**:** Neural Network Autoregression
PoS	**:** Proof of Stake
PoW	**:** Proof of Work
ReLU	**:** Rectified Linear Units
RNN	**:** Recurrent Neural Networks
TVP-VAR	**:** Time-Varying Parameter Structural Vector Autoregression
VAR	**:** Vector Autoregression

SYMBOLS

$\boldsymbol{x}$	: Input signal, Input
$\boldsymbol{y}$	: Output signal, output
$\boldsymbol{\hat{y}_i}$	: Predicted output
$\boldsymbol{x'}$	: Normalized x
$\mathbf{t}$	: Time
$\boldsymbol{n}$	: Length of vector
$\boldsymbol{\Sigma}$	: Summation
$\boldsymbol{r}$	: Correlation coefficient
$\boldsymbol{SS}$	: Sum of squares
$\boldsymbol{R^2}$	: Coefficient of determination
$\boldsymbol{W}, \boldsymbol{U}$	: Weight matrix
$\boldsymbol{f}$	: Function
$\boldsymbol{h}$	: Hidden state value
σ	: Sigmoid function
$\boldsymbol{C_t}$	: Cell state variable
$\boldsymbol{\widetilde{C_t}}$	: Candidate value
$\boldsymbol{i_t}$	: Input gate value
b	: Bias vector

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PREDICTION OF CRYPTOCURRENCY ENERGY CONSUMPTION (AND/OR PRICES) THROUGH THE APPLICATION OF THE MACHINE LEARNING

SUMMARY

One of the most important developments of the last decade is cryptocurrencies. This sector is increasing its popularity and usage areas, with a rising trend. As with every technology, it comes with certain disadvantages along with its advantages, and the disadvantage of cryptocurrencies is the enormous energy consumption of blockchain technology. The energy consumption of Bitcoin, the first example and most famous of cryptocurrencies, is large enough to compete with many countries. This energy consumption is based on Bitcoin mining. Although efforts are made to prevent this energy consumption with processors specially prepared for miners, Bitcoin mining still consumes very high levels of energy. Considering that the majority of this consumption is made from non-renewable energy sources, this is a huge environmental problem.

Another sector that has seen a massive rise in the last decade is artificial intelligence. Artificial intelligence (AI), whose areas of use and skills develop daily, has surpassed classical methods in many areas. With the increase in processing power and access to larger data, artificial intelligence has gained significant momentum and has become perhaps the biggest trend of today. Artificial intelligence applications provide outstanding results for prediction algorithms as well as in every field. Machine learning applications that forecast time series give consistent results and can make sharp predictions. These applications, used in many sectors today, are precious as they make people's work easier or enable them to detect possible problems in advance and take precautions. This project aims to predict Bitcoin's energy consumption, shed light on the future, and create a warning to prevent its adverse effects.

Within the scope of this project, which tried to predict Bitcoin's energy consumption with machine learning applications, firstly, a literature review was conducted, machine learning models that could be used were found, and the factors that caused Bitcoin's energy consumption were examined. During the data collection phase, in addition to

energy consumption data, data on factors that could cause this consumption were also found, and a large data set was obtained. In the project, data from April 2011 until March 2024 was collected, and consumption between December 2022 and March 2024 was tested to be estimated.

Recurrent neural networks (RNN) and long short-term memory (LSTM) were chosen as the models to predict Bitcoin energy consumption. RNN is a suitable model for solving time series forecasting problems like this one. On the other hand, LSTM is a type of RNN developed to obtain even better results on these issues. It was developed to eliminate the problems of gradient explosion and extinction, which are the biggest problems of RNN in this regard.

In this study, the obtained data was first converted to CSV format. The project was developed in the Python environment using the Visual Studio Code compiler. The pandas library was used to import and process the data in CSV format, and the TensorFlow library was used to create and train the models.

Since the data obtained were on different scales, they were normalized to avoid misleading the model and to obtain better results. Normalized data was divided into three for subsequent testing. Historically, 80% of the given time was reserved for training, 10% for validation, and 10% for the testing process, and then the training of the models started. The results were examined, the data and the model's behavior were analyzed, fine-tuning was made, and the parameters were updated accordingly. Coefficient of determination (R^2) and root mean square error of approximation (RMSE) metrics were used to measure the predictions' success after the models were trained. In addition, the predictions and actual values obtained were plotted on a graph to visualize and see the results.

When the graphics and performance metrics obtained as a result of the project are examined, it can be observed that the models predict successfully. As can be seen from here, machine learning applications, especially RNN and LSTM, are successful methods for predicting time series. As written in the previous paragraphs, these results actually carry a warning because Bitcoin's energy consumption is in an upward trend. Solutions such as innovations to reduce consumption or regulations to ensure that consumption is done with renewable energy sources can prevent this trend or reduce its environmental disadvantages.

MAKİNE ÖĞRENİMİNİN UYGULANMASI YOLUYLA KRİPTO PARA ENERJİ TÜKETİMİNİN (VE/VEYA FİYATLARININ) TAHMİNİ

ÖZET

Son on yılın en önemli gelişmelerinden birisi kripto paralardır, bu sektör yükselen bir trendle popülerliğini ve kullanım alanlarını arttırmaktadırlar. Her teknolojide olduğu gibi avantajlarının yanında belli dezavantajlarla gelir ve kripto paraların dezavantajı da blok zinciri teknolojisinin büyük enerji tüketimidir. Kripto paraların ilk örneği ve en popüleri olan Bitcoin'in enerji tüketimi pek çok ülkeyle yarışabilecek büyüklüktedir. Bu enerji tüketimi Bitcoin madenciliğine dayanır. Madenciler için özel hazırlanan işlemcilerle bu enerji tüketiminin önüne geçilmeye çalışılsa da Bitcoin madenciliği halen çok yüksek seviyelerde enerji tüketmektedir. Bu tüketimin büyük çoğunluğunun yenilenemez enerji kaynaklarından yapıldığını düşünürsek bu çok büyük bir çevresel sorundur.

Son on yılda büyük bir yükselişte olan diğer sektör de yapay zekadır. Kullanım alanları ve becerileri her gün gelişen yapay zeka, artık pek çok alanda klasik yöntemlerin önüne geçmiştir. İşlem gücünün artması ve daha büyük verilere ulaşılabilmesiyle yapay zeka çok büyük ivme kazanmış ve günümüzün belki de en büyük trendi haline gelmiştir. Yapay zeka uygulamaları her alanda olduğu gibi tahmin etme algoritmaları için de çok iyi sonuçlar vermektedir. Zaman serilerini tahmin etmek için kullanılan makine öğrenmesi uygulamaları çok tutarlı sonuçlar vermekte ve çok keskin tahminler yapabilmektedir. Günümüzde çoğu sektörde kullanılan bu uygulamalar insanların işini kolaylaştırması veya olası sıkıntıları önceden fark edip önlemler alınabilmesini sağlamasıyla çok değerlidir. Bu projenin amacı da Bitcoin'in enerji tüketimini tahmin edip geleceğe bir ışık tutmak ve yaratacağı negatif etkilerin önüne geçilmesini için bir uyarı oluşturmaktır.

Makine öğrenmesi uygulamalarıyla Bitcoin'in enerji tüketimi tahmin edilmeye çalışılan bu proje kapsamında öncelikle literatür taraması yapılmış, kullanılabilecek makine öğrenmesi modelleri bulunmuş ve Bitcoin'in enerji tüketimine sebep olan faktörler incelenmiştir. Projede 2011 Nisan ayında 2024 Mart ayına kadar olan veriler

toplanmış ve 2022 Aralık ile 2024 Mart arası tarihlerdeki tüketim tahmin edilmeye çalışılmıştır.

Bitcoin enerji tüketimini tahmin etmek için kullanılacak modeller olarak tekrarlayan sinir ağları (RNN) ve uzun kısa süreli bellek (LSTM) seçilmiştir. RNN bu konuda olduğu gibi zaman serisi tahmin etme problemlerini çözmek için çok uygun bir modeldir. Öte taraftan LSTM bu konularda daha da iyi sonuçlar alabilmek için geliştirilmiş bir RNN türüdür. RNN'nin bu konudaki en büyük sorunları olan gradyan patlaması ve yok olması sorunlarını ortadan kaldırmak için geliştirilmiştir.

Bu çalışmada, elde edilen verilen öncelikle CSV formatina getirilmiştir. Proje, Python ortamında geliştirilmiş ve Visual Studio Code derleyicisi kullanılmıştır. CSV formatındaki verileri Python ortamına almak ve verileri işlemek için pandas kütüphanesi, modelleri yaratmak ve eğitmek için de TensorFlow kütüphanesi kullanılmıştır.

Elde edilen veriler farklı birimlerde ve büyüklüklerde olduğu için modeli yanıltmaması ve daha iyi sonuçlar alınması amacıyla normalize edilmiştir. Normalize edilmiş veriler sonradan test edilebilmesi için üçe ayrılmıştır. Verilen %80'i eğitim, %10'u onaylama ve %10'u test süreci için tarihsel olarak ayrılmış ve sonrasında modellerin eğitimine başlanmıştır. Alınan sonuçlar incelenip verinin ve modelin davranışı analiz edilmiş ve bunlara göre ince ayarlar yapılmış, parametreler güncellenmiştir. Modeller eğitildikten sonra elde edilen tahminlerin başarısını ölçmek için determinasyon katsayısı (R^2) ve yaklaşık hataların ortalama karekökü (RMSE) metrikleri kullanılmıştır. Ayrıca görselleştirmek ve çıkan sonuçları görebilmek için elde edilen tahminler ve gerçek değerler bir grafiğe çizdirilmiştir.

Proje sonucunda elde edilen grafikler ve performans metriklerine incelendiğinde, modellerin başarıyla tahmin ettiği gözlemlenebilir. Burdan da anlaşılabileceği üzere makine öğrenmesi uygulamaları, özellikle RNN ve LSTM, zaman serilerini tahmin etmek için başarılı yöntemlerdir. Önceki paragraflarda da yazdığı gibi bu sonuçlar aslında bir uyarı taşımaktadır çünkü Bitcoin'in enerji tüketimi bir yükseliş trendindedir. Tüketimi azaltacak yenilikler veya tüketimin yenilebilir enerji kaynaklarıyla yapılması için regülasyonlar yapmak gibi çözümler bu trendin önüne geçebilir veya çevresel dezavantajlarını azaltabilir.

1. INTRODUCTION

1.1 Purpose of Project

Bitcoin, introduced in 2009 by Satoshi Nakamoto, was the first decentralized cryptocurrency and truly changed the world of digital finance. It eliminates the need for a central authority and allows secure, private dealings through blockchain technology. Popularity has brought not only a wave of opportunities for the development of significant numbers of new cryptocurrencies but also focused attention on crucial problems. The most identifiable major one is that of energy consumption. The Bitcoin blockchain is based on mining, a process in which a group of miners record transactions in the network and receive a reward in return. The method is highly efficient in network security enforcement, but at the same time, it is energy-consuming and computationally intensive. As the environmental footprint of higher energy consumption is added to the increasing global focus on sustainability, the environmental impact from higher energy consumption becomes of paramount significance.

This work seeks to establish the feasibility of machine learning algorithms in the prediction of energy consumption using real-world data. Specifically, the research will consider using recurrent neural networks (RNN) and long short-term memory (LSTM) for this project. The latter two networks are suitable for modeling the time series of data linked to the amount of energy that Bitcoin consumes since they are apt to manage the sequential data. Further, this research could also be directed at the feasibility of indicating and comparing the success of machine learning techniques in practical applications when they are subjected to the interpretation of complex data sets, such as the one we are concerned with in this work, namely, the data set regarding energy consumption in Bitcoin mining. Contributing to the broader field of data science and machine learning., the work focuses specifically on the opportunities and challenges facing the application of advanced analytics in comprehending and assessing energy use. More precisely, the work focuses on the practical application of LSTM and RNN models. Some of the more detailed reviews and analysis of the energy use statistics of Bitcoin mining, the application of specific machine learning models, and an assessment of these models using a particular testing dataset are explained in the following sections. This approach accentuates an attempt of the project to demonstrate and test the possibility of using machine learning algorithms to analyze real-world data rather than to make direct predictions about future trends.

1.2 Project Work Plan

A work plan was prepared to determine the main tasks that needed to be done for the project to be successful and to follow the progress of the project. The work plan comprises seven fundamental processes, which are as follows:literature review, data collection, writing a project progress report, data processing, implementation of ML models, comparison of the performance of the models and results, and writing the project report. This study plan is planned according to the weeks of the 2023-2024 academic year. The work plan is given in Table 1.1.

Table 1. 1 Project Work Plan

#	Task	Responsible Group Member(s)	WEEKS																											
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	Literature Review	Talha Sarlık					X	X	X	X																				
2	Data collection	Talha Sarlık									X	X	X	X	X	X														
3	Writing the project progress report	Talha Sarlık														X	X	X												
4	Data processing	Talha Sarlık															X	X	X											
5	Implementation of ML models	Talha Sarlık																		X	X	X								
6	Comparison of the performance of the models and results	Talha Sarlık																					X	X	X	X				
7	Writing the project report	Talha Sarlık																									X	X	X	X

2. PRELIMINARY RESEARCH

2.1 Literature Review

In this project, machine learning algorithms for time series forecasting will be used to predict Bitcoin energy consumption. Studies have been carried out in the past in these and similar areas, and solutions have been produced for this purpose using various approaches. Past studies were considerably benefited from during the project, and the approaches most suitable for this project were selected. Apart from these, the importance of better understanding the problem and data for the solution has been noticed, and research has been conducted on Bitcoin, blockchain, and mining.

In the long- and short-term prediction of Bitcoin energy consumption [1], bitcoin energy consumption has been approached in various ways, and many variations of RNN have been tried to achieve good results. In this research, beyond using only a specific model and giving results, various models were tried with many different parameters, and these models were compared. Various parameter changes were attempted using Long Short-Term Memory (LSTM), Gated recurrent unit (GRU), and Bidirectional layers to achieve optimal results, and the parameters yielding the best results were documented. This paper has made significant contributions to this project, being one of the most extensive studies in the field. In Trade volume affects bitcoin energy consumption and carbon footprint [2], predictions have been made regarding Bitcoin energy consumption and its environmental impacts. Vektor autoregressive (VAR) algorithm was used for this purpose. In Bitcoin price evolution versus energy consumption; trend analysis [3], predicted Bitcoin price and energy consumption using Multi-Layer Perceptron (MLP). All the parameters used in the paper are explained in detail, which provides a better understanding of this subject. In short-term bitcoin market prediction via machine learning [4], Bitcoin market values were predicted and examined using various machine learning algorithms. Since most of the algorithms used in this paper are considered or used in the project, the information here sheds light on this project and greatly helps the process. Many different algorithms have been used in this paper, especially Artificial Neural Networks

(ANNs) such as Feedforward neural networks (FNN) and various RNNs. These algorithms can be generally listed as follows: FNN, LSTM, GRU, Ensemble models, and tree-based models like random forest and gradient boosting classifiers. In Next-Day Bitcoin Price Forecast [5], an attempt was made to make a prediction based on price again. Autoregressive integrated moving average (ARIMA) and neural network autoregression (NNAR) models are used in this paper. As seen in this paper, while there is a simple algorithm such as ARIMA on the one hand and a complex algorithm such as NNAR on the other, sometimes better results can be obtained with the simpler ARIMA.

When scanning the literature on Bitcoin, mining, and energy consumption, the first paper to be examined is Bitcoin: A Peer-to-Peer Electronic Cash System [6], in which Satoshi Nakamoto published Bitcoin. This paper is a primer on Bitcoin and blockchain technology, and most of what is needed can be learned from it. In an analysis of energy consumption and carbon footprints of cryptocurrencies and possible solutions [7], extensive research has been done on Bitcoin energy consumption. It is a beneficial paper for understanding the problem better. Energy consumption in total and transaction sizes was compared with consumption in similar sizes or areas, and the size of Bitcoin's energy consumption was revealed. At the same time, he explained the technical explanations of everything that causes energy consumption and the hardware used in the mining process. In Energy Consumption and Bitcoin Market [8], the relationship between Bitcoin price and energy consumption is explained, and the relationship between time-varying parameter structural vector autoregression (TVP-VAR) and this duo is expressed in numerical data. In Dynamics of bitcoin prices and energy consumption [9], a similar relationship was sought between price and energy consumption. Unlike the previous one, this paper found different price and energy consumption regimes using threshold regression (TR).

As a result of this literature review, it was aimed to have a deeper understanding of the project and this aim was achieved. Technical understanding of Bitcoin's energy consumption has been established and necessary research has been conducted for time series forecasting. Machine learning algorithms that can be used for forecasting have been found and in-depth research has been carried out on these algorithms.

2.2 Bitcoin Energy Consumption

2.2.1 Technical explanation of Bitcoin energy consumption

In Mining, the main reason for Bitcoin energy consumption, is the main factor that enables the establishment of a decentralized and secure network and is vital for Bitcoin. Miners confirm transactions and add them to the Bitcoin blockchain. Each block depends on the previous and following blocks, and that is why this system is called blockchain (Figure 2.1). Each created block is verified by other miners before being accepted into the blockchain, thus establishing the secure and decentralized structure of Bitcoin. The mining process requires a lot of processing power due to its complex structure, which is the main reason for Bitcoin's energy consumption. Therefore, to understand Bitcoin energy consumption, it is necessary to understand the technical features of mining.

The Proof of Work (PoW) algorithm, the foundation of Bitcoin mining, provides evidence of the process's competitiveness. Miners solve complex mathematic puzzles to confirm transactions and build new blocks. Each puzzle requires finding a nonce, a unique number that, when used in the hash function, results in a hash that meets specific criteria, such as having a certain number of leading zeros. The first miner to solve this sets the block in the blockchain and is further rewarded with newly mined bitcoins. These puzzles are automatically made more or less difficult on average every two weeks, following every new 2016 block, to keep up with the amount of computing work and the increasing computational power that continues to drive the mining race ever stronger.

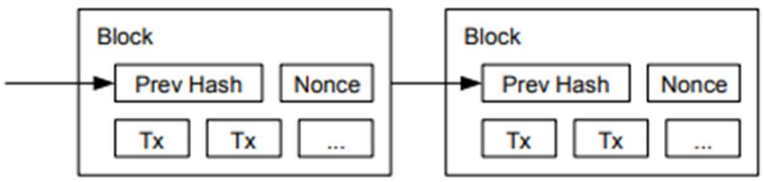

Figure 2. 1: Visualization the structure of blockchain [6]

PoW is designed to purposefully be intensive and competitive in resources. It secures the network by making any aspect of the blockchain computationally hard and, therefore, uneconomical to change. The hardware investment in mining, along with associated electricity costs, is a critical component of this security feature.

Anyhow, this is where the primary energy consumption of Bitcoin mining can be seen: in the course of significant computational effort spat out for each and every process of PoW. Miners must use specialized hardware with built-in ASICs, which are rather good at solving puzzles on the hashing side for mining but also rather heavy in terms of electrical energy use. Whether global in nature, there has always been a debate as to why this has resulted in different mining farms sited in regions of cheap electricity or natural cooling, like cold areas, to minimize costs. A reasonable cause could be the distribution of mining farms, which also lies in the hands of the local regulatory environment, where some of the regions may impose restrictions or tariffs on mining activities that are heavy on energy.

The environmental cost of such mining is enormous, and much of the power, especially in regions where it is generated by coal, goes to carbon emissions. It is this feature that has brought heavy criticism and debates on the sustainability of crypto assets using PoW. Conversely, there is growing interest in alternative consensus algorithms that are less energy-demanding, such as the Proof of Stake (PoS) algorithm.

Technological advances can make the equipment more energy-efficient, thus reducing the energy needed for each Bitcoin transaction. Moreover, the use of renewable energy sources is increasing in a positive correlation with mining activity.

In essence, Bitcoin's energy consumption has everything to do with the mechanics behind the mining process. This process must be carried out to ensure the integrity and decentralization of the Bitcoin network. However, it creates massive environmental challenges that the cryptocurrency community works to overcome through technological innovations and changing the practice of mining.

2.2.2 Analysis of Bitcoin energy consumption

This part will demonstrate and benchmark the scale of Bitcoin's energy consumption to better show its impact on the environment. This analysis not only puts the scale of Bitcoin's energy consumption into perspective but also highlights its impacts compared to traditional financial systems and national energy consumptions.

Bitcoin's energy consumption is often compared to the energy usage of entire countries to illustrate its magnitude. For instance, in some recent estimates, computations related to mining Bitcoins consume an amount of electricity equivalent to mid-sized countries like Sweden or Malaysia. This puts the scale of Bitcoin's energy consumption in explicit terms, and consequently, it is striking that this is not the energy demanded by a whole national economy but just from the network of a single digital currency. This becomes very important in this consideration because, if Bitcoin were a country, it would fall in the top 30 in CO_2 emissions (Table 2.1). The importance of this comparison is brought out in the environmental implications of this cryptocurrency, particularly viewed against the challenge of global climate change, considering that much of this mining activity is undertaken by power sources that are not based on renewable energy sources.

Table 2. 1: Ranking of Bitcoin and Ethereum among countries based on annual electrical energy consumption as of July 2021 [7]

Rank	Country and Region	Energy (TWh)	Share (%)
0	World	23,398.00	100.00
1	China	7,500.00	32.05
2	U.S.A	3,989.60	17.05
22	South Africa	210.30	0.89
23	Bitcoin + Ethereum	190.13	0.81
24	Thailand	185.85	0.79
25	Poland	153.00	0.65
26	Egypt	150.57	0.64
27	Malaysia	147.21	0.62
28	Bitcoin	135.12	0.57
29	Sweden	131.79	0.56

Comparisons of energy consumption in a single Bitcoin transaction and single transactions by traditional Visa come to the striking differences from this: one single Bitcoin transaction could provide energy consumption equivalent to tens of thousands of Visa transactions (Table 2.2).

This high disparity arises from the fact that every single Bitcoin transaction has to gain the agreement of the network miners, while the Visa transactions are conducted through a centralized infrastructure that is very energy-efficient.

Table 2. 2: Comparison of energy consumption and carbon footprints per transaction for Bitcoin, Ethereum and Visa as of July 2021 [7].

Transaction method	Emission (KgCO_2)	Energy consumption (kWh)
Bitcoin	844.13	1777.11
Ethereum	59.55	125.36
Visa	0.00045	0.0015

The type of mining hardware in use makes a huge difference to the overall energy consumption of the Bitcoin network. ASIC miners are the hardware most efficiently mining Bitcoin commercially (Table 2.3). They were designed solely to solve Bitcoin's cryptographic problems and, compared to previous hardware generations for efficiency in hash rates, represent a vast improvement in energy use. Their absolute energy consumption is still vast, and the technology improvement, however considerable, stands to be of note. The efficiency of these miners is measured in joules per terahash, which has been improving over time but still represents large-scale use of energy when deployed by thousands of miners around the globe. Scalability guarantees that as Bitcoin grows, it is time to adopt more sustainable mining practices imperative. This includes mining with the use of renewable energy sources and the continuous improvement of the energy efficiency of mining hardware. Innovations in the line of more efficient ASIC models and the potential shift of the network toward more energy-friendly consensus mechanisms, like PoS (Proof of Stake), are ways to tackle the possible worries against environmental concerns.

Table 2. 3: Performance metrics of different mining devices [7].

Hardware type	Mining rate (GH/s)	Efficiency (J/GH)	Min. Energy Consumption (TWh)
CPU	0.01	9000	11,000
GPU	0.2–2	1500–400	3,000
FPGA	0.1–25	100–45	250
ASIC	44,000	0.05	1.46

In fact, the analysis does seem to run counter against Bitcoin energy consumption, showing how it correlates with significant global activities but underlining importance to the future of cryptocurrency in environment-sound manner, mined hardware, technological innovation, and regulatory measures.

2.3 Model Selection

A literature review was conducted in advance to investigate the identified machine learning models that can be used as predictors for forecasting Bitcoin energy consumption within this study. Several models have been considered in terms of the purpose of the study and the way they can handle time series data. After careful consideration of their functionality and limitations, the Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) models were determined for this study. These models are singled out from others due to their demonstration of incomparable capability in capturing temporal dependency and irregularities within a complex dataset, hence suitable to the predictive analysis needed in this project.

3. DATA ANALYSIS

3.1 General Information About Dataset

The data utilized in this study were sourced from two distinct repositories. The first and most crucial dataset is the Bitcoin energy consumption dataset of The Cambridge Bitcoin Electricity Consumption Index (CBCEI). This resource contains all data of Bitcoin energy consumption, which is the project's main purpose, from 2010 to the current date. As said in previous sections, some factors affect the energy consumption of Bitcoin mining, and Bitcoin does not have a centralized structure, making it impossible to calculate Bitcoin's energy consumption precisely. For this reason, CBCEI prepares the dataset in three different columns. These are minimum, maximum, and estimated energy consumption columns. Data is visualized in Figure 3.1.

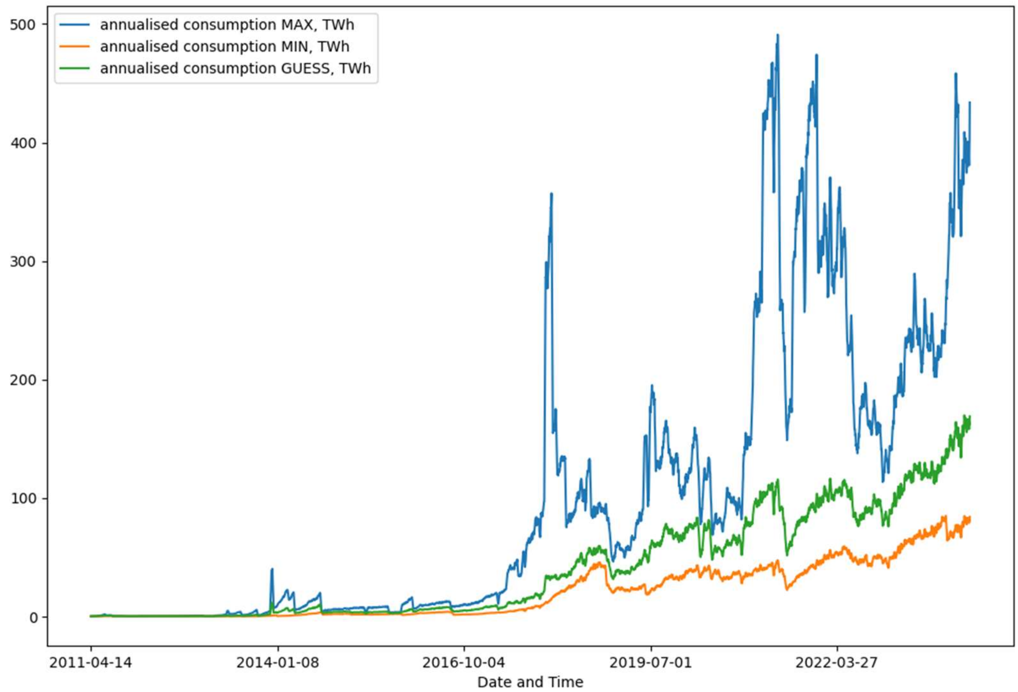

Figure 3. 1: Plot of CBCEI dataset

Since there are many different features that directly or indirectly affect Bitcoin energy consumption, this has made a different dataset more necessary in the project. This dataset was accessed thanks to the BitInfoCharts site, which shares many essential features about Bitcoin. The dataset obtained from this source was used to understand the data or develop the model.

Thanks to the data obtained from these two sources, a large dataset of our target, Bitcoin energy consumption, and the features that affect it were obtained. All data was converted to CSV format and loaded into Python with the help of the pandas library.

3.2 Data Processing

3.2.1 Feature Selection

The data obtained during the dataset collection process has many features. Using all of these features will increase both processing time and model complexity. Data that slightly affect Bitcoin energy consumption will cause these adverse effects and may also negatively affect the model's predictive power. Having a larger dataset does not necessarily guarantee better results. Therefore, a correlation was applied to the dataset. Results of the correlation shown in Table 3.1. Correlation is a statistical tool used to determine the amount and direction of correspondence between two or more variables. One of the statistical concepts is correlation, which depicts the relation of the variables. Such values are between the solid negative correlation shown by -1 and the strong positive correlation shown by +1; the values are close to 0 and indicate no substantial linear correlation. However, the essential thing to note is that where two variables are highly correlated, this does not necessarily indicate that one causes changes in the other, meaning it just indicates that the two variables are related. Usually, the correlation coefficients are obtained using Pearson's correlation method, especially for linear relationships.

$$r = \frac{\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{x})^2 \sum_{i=1}^{n}(y_i-\overline{y})^2}} \tag{3.1}$$

This formula represents the Pearson correlation coefficient, r, which measures the linear relationship between two variables, x and y. Here, x_i and y_i are the individual sample points indexed with i, $\overline{x}$ and $\overline{y}$ are the means of the x and y datasets, respectively, and n is the number of data points.

This is a critical statistical tool for understanding trends and relationships in data, helping the researchers further analyze and test hypotheses. By examining the table resulting from the correlation, some features were eliminated, and the final version of the dataset was created.

Table 3. 1: Correlation between energy consumption and features.

Correlation With the Data	Annualised Consumption MAX, TWh	Annualised Consumption MAX, TWh	Annualised Consumption Guess, TWh
Bitcoin Price	0.955383	0.726137	0.819052
Transactions	0.488695	0.626445	0.639906
Sent Adresses	0.626394	0.677014	0.705227
Difficulty	0.707030	0.921739	0.919408
Hashrate	0.706863	0.919915	0.917439
Mining Profitability	-0.465893	-0.641652	-0.632753
Market Cap	0.952846	0.739536	0.829515
Active Adresses	0.719358	0.690795	0.736919
Average Transaction Value	0.652568	0.345072	0.423204

3.2.2 Data normalization

Normalization of data is thus a fundamental step in pre-processing for all machine learning algorithms, especially for models such as Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) that are very sensitive to the scales of features. Otherwise, features with too large a scale would dominate the solution and become the most essential part of training the model, leading to inefficient learning and biased predictions. Thus, without normalization, it could lead to inefficient learning and biased predictions if features with larger scales take over and disproportionally affect the model.

$$x' = \frac{x - \mathrm{m}\quad(x)}{\max(x) - \min(x)} \tag{3.2}$$

Here, x is the an value, $\min(x)$ is the minimum value of the feature across all data points, $\max(x)$ is the maximum value of the feature across all data points, x' is the normalized value.

In this project, we used the MinMaxScaler to normalize our data, scaling features into a specified range—in this case, between 0 and 1. What MinMaxScaler does is normalize the features to the range set between the minimum and maximum of that feature. This method is well suited to representing the original data distribution's shape and does not distort the difference in the range of values. Scaling features to a [0,1] range makes the MinMaxScaler ensure that the models are free of bias by the natural variance of input data; thus, they present better stability and quicker convergence during the learning process.

3.2.3 Incorporating time lags

In time series analysis, introducing lags is instrumental for infusing historical depth into the dataset, enriching the contextual framework within which predictive models operate. In the current study, data have been prepared to forecast Bitcoin energy consumption with a 60-day lag. A lag of 60 days was added methodically in preparing the data for Bitcoin energy consumption forecasting in this current study. The procedure involves shifting the data points by 60 days in hindsight and hence accounts for the preceding two months of data in explaining the future period.

A 60-day lag is chosen because it best captures the seasonal trends and long-run dependencies within the energy consumption pattern of Bitcoin, which is responsible for the structure of the time series data. Including this information from past observations into the entire sequence of the past of the LSTM and RNN models allows the model to sense and adapt to the underlying fluctuations in energy consumption linked with the Bitcoin mining process. It is a design that uses historical data to improve prediction accuracy and align the operational features in the input with cycles that likely affect Bitcoin's energy usage. Therefore, an advanced 60-day lag is an essential aspect of refining the forecasting power of our models and further captures both the cyclical and stochastic components of the data-generating process.

3.2.4 Data distribution

An effective strategy of partitioning the data will be critical to assessing model performance. In this study, the data distribution is based on an 80-10-10 partitioning scheme with respect to training, validation, and test sets. Data distribution is visualized in Figure 3.2. The method will ensure that 80% of the data goes into training the models to learn and adapt to the complexities in Bitcoin's patterns of energy use.

The rest of the data is afterward partitioned accordingly: 10% for the validation process and 10% for the testing process. This, therefore, paves the way for the validation set to participate in the tuning process of the models and provides the opportunity for sandbox optimization of hyperparameters and configurations of the models without fear of overfitting. The subdivision is of immense importance, for it will assure that any increase of units in the learning ability of the model is generalized to unconstrained data and is, in essence, a product of a good strategy of modeling and not idiosyncrasies of the training data.

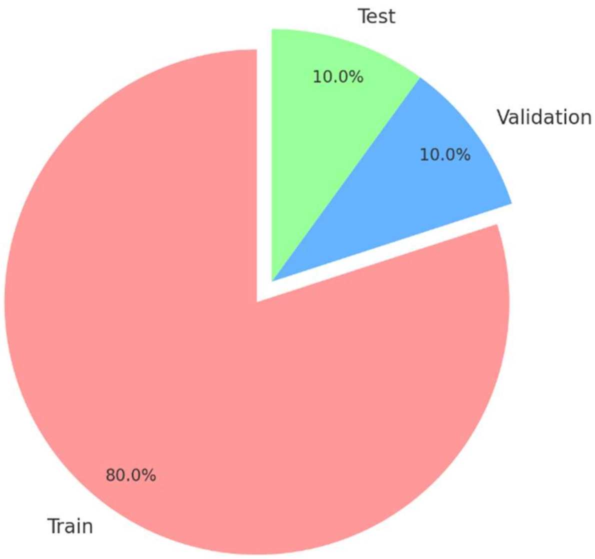

Figure 3. 2: Data distribution

The test set, although the small partition, is definitely the most significant because it is the model's final benchmark. The data volume is constrained even further, limited to only 10% of the entire data, to be used only once to assess model performance. These will serve as a new, independent source of information simulating how the model would perform under real-life operational conditions. Through such a strictly partitioned strategy, a robust evaluation framework will be built, whereby accuracy and reliability in prediction are established before the models are practically deployed.

4. FORECASTING MODELS

4.1 Selected Models

4.1.1 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are the class of artificial neural networks that can model sequential data. The difference here is that an RNN, as opposed to a classical feedforward neural network, is able to hold the 'memory' of the previous input due to its internal state, or hidden layers, and is therefore capable of showing dynamic temporal behavior. In this regard, RNN is appropriate for problems in which the context of earlier data is significant in predicting, such as time-series forecasting and natural language processing.

RNNs are powerful in sequence prediction problems because they can build and hold a model of context in the input sequence to predict the next point. RNNs can learn patterns in time series data, which makes it possible to predict future points in the series. This goes directly to the core of our project goal: forecasting Bitcoin energy consumption.

Despite their advantages, RNNs often face some technical problems, such as vanishing and exploding gradients. The vanishing gradient problem occurs when the gradients of the network's weights are updated to minimal values, slamming the brakes on further training by prohibiting further weight updates. The exploding gradient does occur when the gradients become really extensive, which leads to weight updates that are too dramatic, sending the network into diverging behavior.

In this study, RNNs were used for the prediction of Bitcoin energy consumption. The inputs were trained on historical data ranging from years, where each data point represents energy consumption regarding Bitcoin mining activities in a day. Furthermore, the application of RNNs in this study exploits the recursive nature of the model used, which usually results in better results when learning the finer details within the varied and repetitive structure of energy consumption data in time series.

An RNN is a sequence-processing model, which means it processes inputs in the order they are given and maintains a state that summarizes the information it has seen so far. This is a fundamental departure from conventional neural networks, which treat all inputs independently.

The RNN's ability to update its state with each sequential input data is what gives it its unique power and versatility.

The basic unit of computation in an RNN is a neuron that has a self-connection, which forms a loop allowing information to persist. In mathematical terms, at each timestep t, the hidden state h_t of the RNN is updated by:

$$h_t = f(W \cdot h_{t-1} + U \cdot x_t + b) \tag{4.1}$$

Here, x_t is the input at time t, h_{t-1} is the hidden state from the previous timestep, which serves as the "memory" of the network, W and U are weight matrices for the hidden state and input, respectively, b is a bias term, f is a non-linear activation function, typically tanh or ReLU.

This update to the hidden state is carried on as the sequence is processed in forward pass, with the network being able to build an increasingly more comprehensive understanding of the data as it receives more inputs. The final state h_t after the entire sequence is processed can be used to make predictions (Figure 4.1).

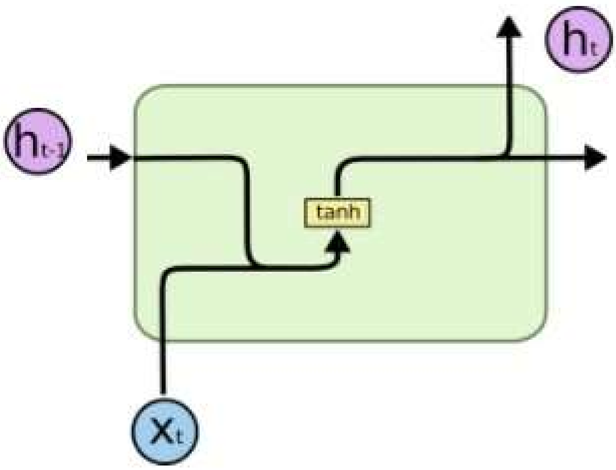

Figure 4. 1: Structure of RNN cell [10]

RNNs are trained so that the parameters W, U and b best minimize a loss function, typically through backpropagation. However, RNNs modify the standard backpropagation algorithm to handle sequences and thus implement backpropagation through time (BPTT). In BPTT, the

RNN is unrolled through time and then the standard backpropagation technique is applied. Gradients are calculated for each time step, and weights are updated.

4.1.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a kind of advanced Recurrent Neural Networks, specially designed to counter the problems of traditional RNNs, mainly dealing with learning long-term dependencies. They are well suited for sequence prediction where the dependency on history can span long periods, such as in the case of Bitcoin energy consumption.

In this regard, in the context of predicting Bitcoin consumption, LSTMs capture short-term fluctuations and long-term trends, which are pivotal to the predictions. Their selective ability to remember and forget information allows an LSTM model to focus on significant temporal patterns in energy usage data, thus making them effective in this context.

However, with this comes a computational and operational challenge; they are more computationally resource-intensive compared to their simpler counterparts and demand the careful tuning of parameters and training methods in order to realize their full potential. The other critical challenge is that the generalizability maintenance, when the LSTM model does not overfit the historical data, is critical.

This project will apply the LSTM model to our dataset to predict Bitcoin energy consumption. In this dataset, each data entry represents daily consumption, which, naturally, exhibits some patterns and dependencies over time. Therefore, an LSTM model emerges as an excellent choice for accurate sequence prediction and robustness of tools for predicting future needs, providing reassurance about the suitability of this approach.

Long Short-Term Memory (LSTM) networks were introduced to enhance the capability of typical recurrent neural networks by introducing a highly complex gating mechanism and a special cell state (Figure 4.2). The LSTM architecture is unfolded into three main gates: input, forget, and output. These gates regulate the information flow throughout the network.

Forget Gate: This gate decides which information is discarded from the cell state. It applies a sigmoid function $\boldsymbol{\sigma}$ to determine the retention rate at each timestep:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4.2}$$

Input Gate: Simultaneously, the input gate decides which new information from the current input $\boldsymbol{x_t}$ is stored in the cell state. It involves two parts: a sigmoid gate that decides which values to update and a tanh layer that creates a vector of new candidate values:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4.3}$$

$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4.4}$$

Cell State Update: The cell state $\boldsymbol{C_t}$ is then updated by forgetting the decided old information and adding the new candidate values:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \tag{4.5}$$

Output Gate: Finally, the output gate determines which parts of the cell state are output to the next layer or used as the final prediction at the timestep. This gate filters the cell state through a sigmoid function to decide which parts are used, and then applies a tanh function to the cell state before multiplying it by the sigmoid gate's output:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{4.6}$$

$$h_t = o_t * \tanh(C_t) \tag{4.7}$$

In each, the LSTM gate works in conjunction with a set of weights represented by W and a bias represented by b and is, in turn, learned during training by backpropagation, which is trained to work with sequences of data using backpropagation through time (BPTT). Combining the gating mechanisms with the cell state and input/output transformations allows a powerful representation of temporal dynamics. Associating these gates with the quick storage and retrieval of information in memory is very useful for tasks in which both recent and more distant history are essential.

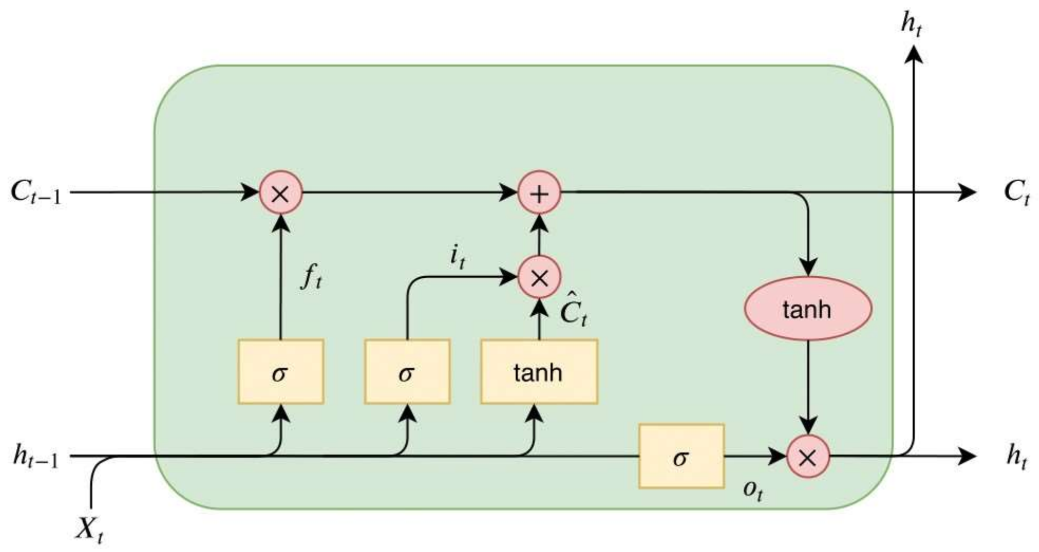

Figure 4. 2: Structure of the LSTM cell [11].

For every increment of the forward pass, these gates take in inputs with information in the previous state to arrive at effectively updating the current state and hence output generation. This fine-grained gating mechanism allows LSTMs to alleviate the vanishing gradient problem that plagues traditional RNNs, thus enhancing the model to learn from data when input from several time steps back is still important.

LSTMs are trained with a variant of BPTT, which takes into account the intricate interplay of the gates and state machinery of the LSTM to ensure that, during training, the way in which the model updates its parameters is optimal and shall result in reducing the loss function, therefore doing a better job of future predictions on hitherto unseen data points.

4.2 Performance Metrics

4.2.1 Root mean square error (RMSE)

It is widely used as a statistical measure to assess the performance of regression models by the magnitude of prediction errors. It quantifies the square root of the average of the squared differences between the predicted values and the observed actual outcomes. RMSE measures the magnitude of error with units of the variable of interest, conditionally making it a good measurer of the model's accuracy. An RMSE value represents less performance in the model and, therefore, less accurate predictions. One of the most noteworthy features of RMSE is its sensitivity toward outliers because it heavily penalizes significant errors by squaring the differences.

The RMSE is mathematically represented as the square root of the average of the squared differences between the predicted and actual values:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.8}$$

Here, $\boldsymbol{n}$ denotes the number of observations, y_i represents the actual values, $\hat{y}_i$ denotes the predicted values, Σ indicates the summation over all observations.

In practical setups, understanding and minimizing RMSE can lead to a massive increase in the reliability of models and the decisions based on them. In essence, RMSE holds great value in testing the predictive validity of regression models, more so in data-rich environments where a high level of precision counts. More than just an academic interest, its application throws light and gives critical insight into the model performance in a real-life scenario.

4.2.2 R-Squared

R-squared refers to the statistical measure of the proportion of variance in the dependent variable that is predictable from the independent variables. R-squared values are always between 0 and 1, and a higher value usually means a better fit to the data. A value of 0 for this means the model explains none of the variability, while for 1 the model explains all the variability of the dependent variable, respectively, meaning a perfect fit. It is calculated as:

$$R^2 = \mathbf{1} - \frac{\boldsymbol{SS_{res}}}{\boldsymbol{SS_{tot}}} \tag{4.9}$$

where $\boldsymbol{SS_{res}}$ is the sum of squares of residuals and $\boldsymbol{SS_{tot}}$ is the total sum of squares.

R-squared is very helpful because it helps to determine how well a model describes the observed data. It is not acceptable to use it solely because several important qualities are missing that help establish whether the model is good and whether the predictions are unbiased. Generally, it is used in the presence of other metrics, such as RMSE and the adjusted R-squared, to judge model performance. It is useful in cases of continuous data, in which one wants to predict some kind of outcome of interest specifically in the fields of finance, economics, and environmental science.

5. IMPLEMENTATION

5.1 RNN

5.1.1 Model structure

The model was created using the Tensorflow library in Python. It has 64 cells in the input layer, 64 and 32 cells in the hidden layers, respectively, and 1 cell in the output layer. Rectified linear units (ReLU) is used for the activation function in the layers. The Adam optimizer and mean-square error loss were used for compiling the model. Finally, the model was trained with 30 epochs and 16 batch size.

5.1.2 Results

After the training of the model was completed, a prediction was made for a test interval of approximately 15 months and these results were visualized.

For minimum Bitcoin energy consumption, the RMSE was 2.0743 and the R^2 score was 0.9618.

The plot of the predicted and actual energy consumption values is shown in Figure 5.1.

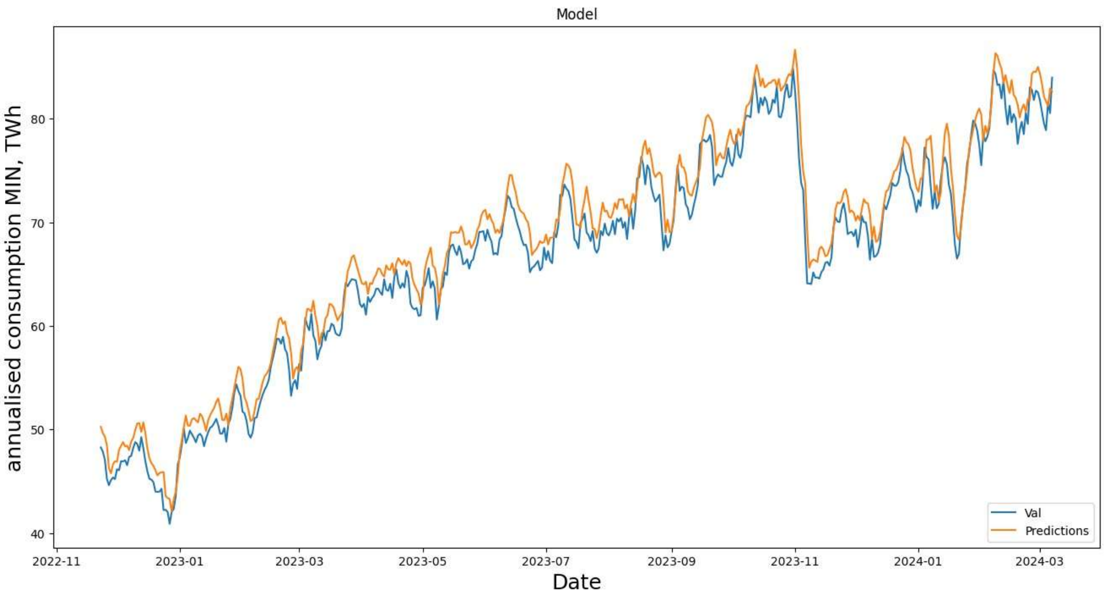

Figure 5. 1: Predicted (RNN) and actual minimum Bitcoin energy consumption

For maximum Bitcoin energy consumption, the RMSE was 8.2967 and the R^2 score was 0.9895.

The plot of the predicted and actual energy consumption values is shown in Figure 5.2.

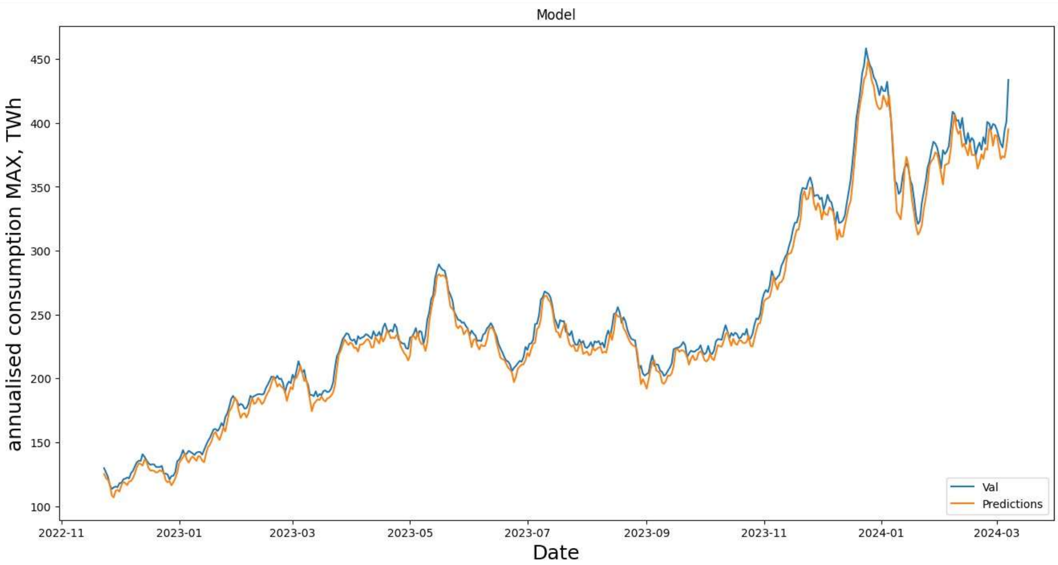

Figure 5. 2: Predicted (RNN) and actual maximum Bitcoin energy consumption

For estimated Bitcoin energy consumption, the RMSE was 4.4078 and the R^2 score was 0.9616.

The plot of the predicted and actual energy consumption values is shown in Figure 5.3.

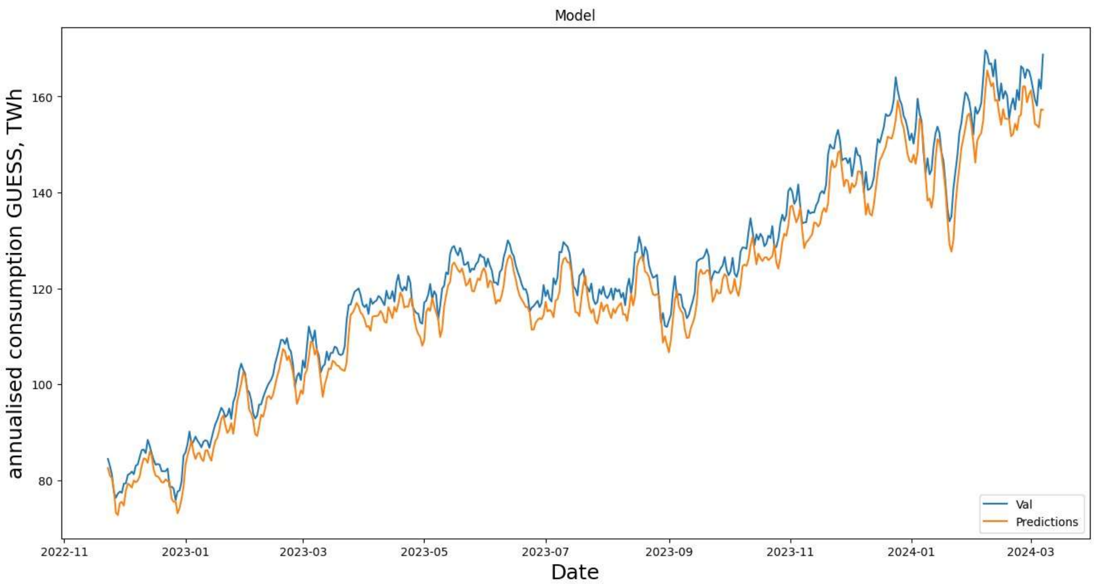

Figure 5. 3: Predicted (RNN) and actual estimated Bitcoin energy consumption

5.2 LSTM

5.2.1 Model structure

The model was created using the Tensorflow library in Python. It has 64 cells in the input layer, 64 and 32 cells in the hidden layers, respectively, and 1 cell in the output layer. Tanh function is used for the activation in the layers. The Adam optimizer and mean-square error loss were used for compiling the model. Finally, the model was trained with 30 epochs and 16 batch size.

5.2.2 Results

After the training of the model was completed, a prediction was made for a test interval of approximately 15 months and these results were visualized.

For minimum Bitcoin energy consumption, the RMSE was 1.9635 and the R^2 score was 0.9658.

The plot of the predicted and actual energy consumption values is shown in Figure 5.4.

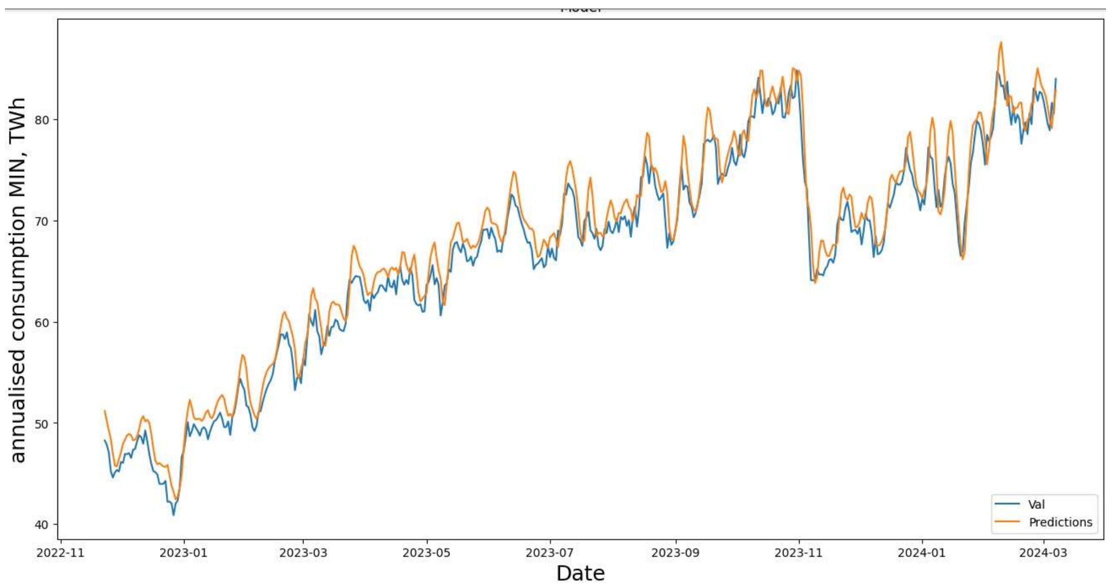

Figure 5. 4: Predicted (LSTM) and actual minimum Bitcoin energy consumption

For maximum Bitcoin energy consumption, the RMSE was 5.5764 and the R^2 score was 0.9952.

The plot of the predicted and actual energy consumption values is shown in Figure 5.5.

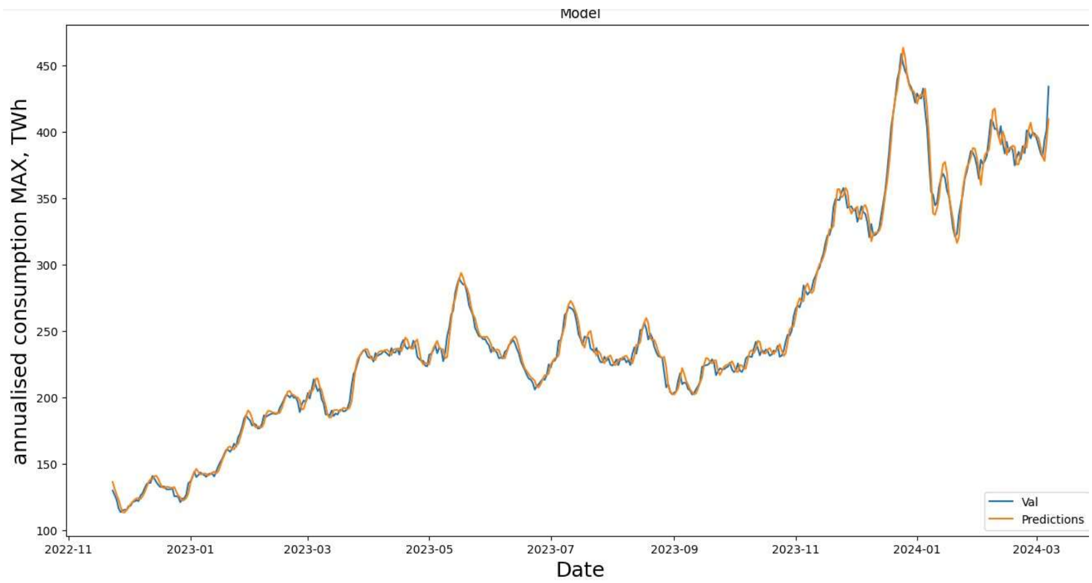

Figure 5. 5: Predicted (LSTM) and actual maximum Bitcoin energy consumption

For estimated Bitcoin energy consumption, the RMSE was 4.5067 and the R^2 score was 0.9599. The plot of the predicted and actual energy consumption values is shown in Figure 5.6.

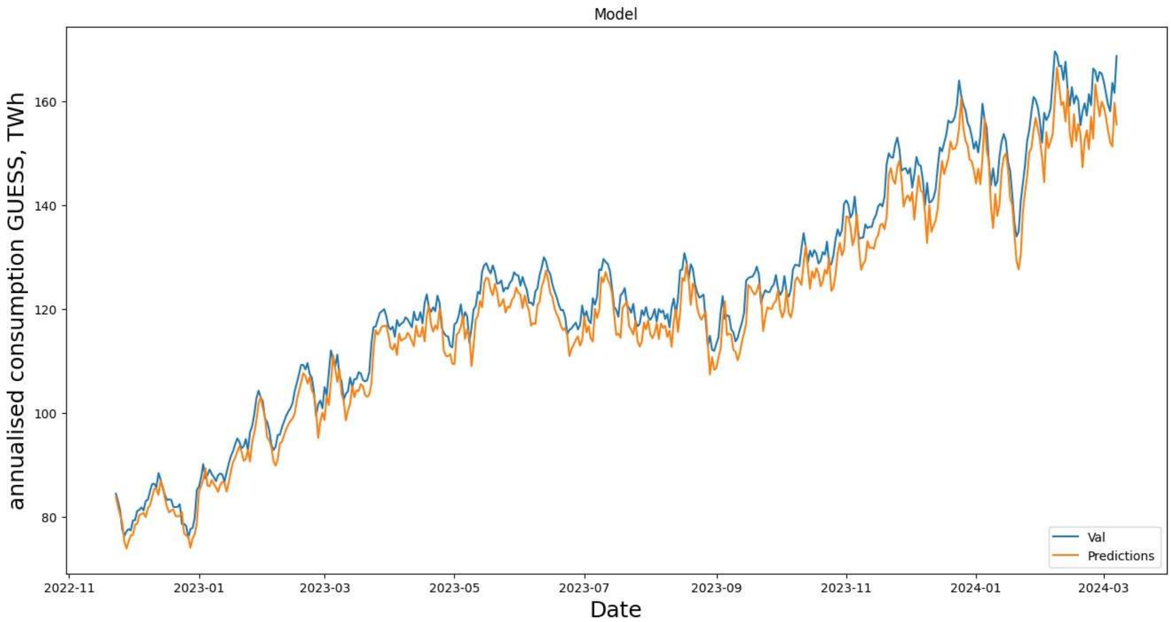

Figure 5. 6: Predicted (LSTM) and actual estimated Bitcoin energy consumption

5.3 Comparison

Both machine learning models developed in the project achieved successful results. Since the results are very close, it is not possible to describe one model as better than the other. R^2 and RMSE values obtained as a result of applying the models are given in Table 5.1.

Table 5. 1: Comparison of performance of models.

Bitcoin Energy Consumption	RNN		LSTM	
	R^2	RMSE	R^2	RMSE
Minimum	0.9618	2.0743	0.9658	1.9635
Maximum	0.9895	8.2967	0.9952	5.5764
Estimated	0.9616	4.4078	0.9599	4.5067

6. REALISTIC CONSTRAINTS AND CONCLUSION

6.1 Practical Application of this Project

Bitcoin is a revolution for the world. Being able to make secure transactions without central management is a game-changer for the financial sector. However, providing these conditions leads to too much energy consumption today. In this project, Bitcoin's energy consumption was examined, and models were developed to predict it. Being able to predict Bitcoin energy consumption allows the possible trend of the data to be observed and precautions to be taken.

6.2 Realistic Constraints

The feasibility of a project depends on its positive effects outweighing its adverse effects. This section will explain the project's applicability to real life**.**

6.2.1 Social, environmental and economic impact

As explained in the report, the environmental and economic effects of Bitcoin energy consumption are significant. Being able to predict this data is precious in reducing or preventing adverse effects. Based on the models and results obtained in this project, this project and future work may create significant impacts in social, environmental, and economic fields.

6.2.2 Cost analysis

The project was implemented in computer environment. The computer programming language used for this project is Python, an open-source programming language available for free on the official website. Therefore, the project does not have any costs other than labor costs. The labor cost/hour determined by the Union of Chambers of Turkish Engineers and Architects is currently 221.87 TL. When the weekly working hours are planned as 15 hours per week, the total cost will be 221.87 TL × 15 hours × 27 weeks = 89857.35 TL.

6.2.3 Standards

There is no standard required in this project. Engineering ethics standards were followed**.**

6.2.4 Health and safety concerns

There were no health or risk-related problems during the project or at the end of the project.

6.3 Future Work and Recommendations

In future work, the obtained models can be improved, and better results can be obtained. Different models can be developed, or a hybrid model can be developed by combining existing models. Apart from these, the dataset can be improved, and new features can be added if possible.

6.4 Conculusion

This project has explored the capability of advanced machine learning techniques, specifically Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, in forecasting Bitcoin energy consumption. These models have been demonstrated to capture the short-term fluctuations and long-run trends in Bitcoin energy use. In general, our results indicate that this class of models performed well on this type of time series. The models were assessed using the essential metrics, RMSE and R-squared, which provided significant help in quantifying their predictive accuracy and fit.

Thorough training, validation, and testing were conducted to ensure that the models were accurate, did not cause overfitting, and were more reliable for practical applications. Conclusions from this project highlight the strong potential that machine learning has to assist in planning and managing resources in Bitcoin mining in the face of growing concern about times when the amount of energy consumed is increasing. Finally, this study not only confirms the possibility of using high-dimensional machine-learning models for the prediction of Bitcoin energy consumption but also serves as a reference for further innovations for the sustainability and efficiency of cryptocurrency mining operations across the globe.

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Skills: Machine Learning, Deep Learning, Artificial Intelligence, Data Science, Python, C, C++, Linux, Data Structures & Algorithms, Signal Processing, Object-Oriented-Programming

Experience:

Arçelik Global – Network and Telecommunications Intern 07/2023 – 09/2023

- Contributed to the enhancement of the company's network infrastructure.
- Assisted in implementing strategies for network improvement and control.
- Acquired hands-on experience in troubleshooting and resolving network issues promptly.
- Stayed updated on emerging technologies, actively participating in their implementation for optimized network performance.

PoiLabs – Machine Learning Engineer Intern 05/2022 – 02/2023

- Actively assisted in keeping up with the latest trends in artificial intelligence, contributing to algorithm improvement and exploring advancements in image processing.
- Staying informed about current AI developments through academic publications and industry sources.
- Participated in the application of new technologies to address challenges in the field.

CarrefourSA – Dijital Transformation Intern 08/2022 – 09/2022

- Software development focused on data processing and data engineering.

Extracurricular:

Young Guru Academy (YGA) Global Impact University’22 Volunteer

- YGA raises double-winged young individuals who are conscience and competent to raise hope for the future. Selected from thousands of applicants and narrowed down into 20 students to be raised as a selfless leader in this non-profit global organization to use my competence in innovations that benefit humanity.
- Main logistics responsible of YGA 2022 Summit.
- Actively participated in YGA's Science Movement, a nationwide social responsibility project aiming to foster a love for science among children in rural schools across Turkey. Contributed to the Bilim Seferberliği initiative by visiting multiple village schools, distributing Science Kits, and facilitating hands-on learning experiences to promote scientific curiosity and awareness of the latest technologies.

EESTEC LC Istanbul

- International Event Head Organizer 09/2023 - 06/2024
    - Successfully spearheaded the coordination of organizing committees for international events within the student club.
    - Established and maintained effective communication between the Organizing Committee and the board, facilitating a cohesive working relationship.
    - Managed the selection of event participants and provided guidance throughout the entire process.
    - Demonstrated leadership by managing the entire event process, from planning to execution, ensuring alignment with club standards and objectives.
- IT Team Coordinator 07/2022 - 07/2023
    - Established and led an effective IT team, providing leadership in software development projects and conducting educational workshops.
    - Organized impactful panels and interviews on software development, fostering knowledge exchange and networking opportunities.
    - Assumed overall responsibility for club IT tasks, including team management, system maintenance, and implementing technological solutions for enhanced efficiency.

EESTEC 09/2022-07/2023

IT Admins Team Member

- Maintain the sustainability of the association’s technical infrastructure.

IT Knowledge and Education Team Member

- Developing strategic plans, templates, guides and organizing learning activities.