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Taming energy and electronic waste generation in bitcoin mining: Insights from Facebook prophet and deep neural network

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ABSTRACT

The Bitcoin mining hosted in the blockchain network consumes enormous amounts of energy and generates electronic waste at an alarming rate. The paper aims to model and predict the future values of these two hazardous variables linked to conventional Bitcoin mining. We develop two predictive models using Facebook's Prophet algorithm and deep neural networks to identify and explain energy consumption and electronic waste generation patterns. The models rely on several explanatory features linked to the blockchain microstructure and the Bitcoin marketplace. We assess the predictive performance of the two models based on daily data of energy consumption and electronic waste generation and eleven key input features. We use local interpretable model-agnostic explanation (LIME) and Shapley additive explanation (SHAP) for explaining how these inputs can predict and control energy consumption and electronic waste generation. The findings assist in accurately estimating the future figures of energy discharge and electronic waste accumulation in the present Bitcoin mining setup. The study also reveals the block size to be the major driver.

1. Introduction

When reading business and financial press, it is hard to avoid the onslaught of blockchain technology. Investors worldwide have been attracted to so-called "Bitcoin mining" – creating new Bitcoin by solving computational problems. While providing potentially lucrative investment opportunities (Scharnowski, 2021), Bitcoin mining relies on energy-intensive hardware (Nazifi et al., 2021) and is significantly contributing to the rise in environmental footprint through electronic waste (E_waste) generation and energy consumption (Truby, 2018; Das and Dutta 2019; Jana et al., 2021). The quantum of energy consumption and speedy E_waste generation in the form of computer hardware and machines that are unwanted, obsolete, and non-profitable have significantly augmented the environmental footprint, which is now threatening the sustainability of Bitcoin. The environmental challenges brought forth by Bitcoin mining are only underscored by the attractiveness and growth of widely adopted blockchain technologies (de Villiers et al., 2021; Balasubramanian et al., 2021; Kamble et al., 2021). Blockchain technology is currently emerging as a critical innovation with strategic importance to anyone managing transactions (Garg et al., 2021; Schlecht et al., 2021; Tandon et al., 2021).

Bitcoin mining involves solving computationally complex cryptographic puzzles linked to blockchain transaction verification, which requires high-end and energy-intensive computational systems for extended durations (Bitcoin Energy Consumption Index, 2021). The empirical evidence suggests that energy consumption is not the only weakness of the Bitcoin mining process (de Vries, 2019). Due to excessive returns, the growing attractiveness of Bitcoin mining has been engaging many participants in mining competition. As a result, the mining process is becoming extremely competitive, demanding the deployment of state-of-the-art computer systems at a rapid pace. The specialized systems have triggered the old to move to oblivion, resulting in large amounts of E_waste. Excess E_waste and energy consumption contribute to the alarming rise in the environmental footprint linked to the Bitcoin mining process. For example, a single Bitcoin transaction creates more than 80 gs of E_waste (Bitcoin Electronic Waste Monitor, 2021). The rapid increase in carbon footprint (de Vries, 2018) has been detrimental to the environment vis-à-vis population health. Therefore, there is an urgent need for research that quantify the hazardous effects, model the evolutionary patterns, and identify the key antecedents that drive the E_waste generation and energy consumption due to Bitcoin mining.

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The hazardous effects of Bitcoin mining on the environment and sustainability have surged among academics and practitioners. For example, there have been calls for alternative frameworks for Bitcoin mining that can reduce energy consumption and E_waste generation (Vranken, 2017; Li et al., 2019; Malfuzi et al., 2020). Specifically, there is a shortage of research to identify the key drivers responsible for E_waste accumulation and growing energy consumption to combat their adverse effects. Therefore, it is critical to perform predictive analysis to control the explanatory features to accomplish the goal. The literature so far reports the work of Lally et al. (2019) that models the adverse environmental ramifications due to E_waste generation from Bitcoin mining. Their findings explained how the accumulation of computer waste and other digital raw materials had been piling up on the Columbia Riverbank. The lack of studies for identifying the inherent patterns connecting salient features of blockchain microstructure and Bitcoin mining manifested through the excess energy consumption, and E_waste generation has motivated us to undertake the present work.

The contribution of this paper is threefold. Firstly, we address a significant research gap by defining a robust framework for estimating precise energy consumption forecasts and E_waste generation by designing an integrated and effective predictive architecture of Bitcoin mining. Accurate estimation of these variables' future trends can assist in framing strategies and allowing for preventive measures. Secondly, this work contributes methodologically by developing an AI-driven predictive modeling framework. We critically evaluate the algorithm's efficacy and perform comparative analysis with a deep neural network (DNN). Thirdly, explainable AI has been leveraged to comprehend the role of pertinent independent features in driving the hazardous effects of Bitcoin mining. The outcome of explainable AI can help control the key exogenous features for taming energy consumption and E_waste generation. The results could potentially suggest how much effort to put on what levers to manage dangerous implications. Policies can also be formulated to monitor the significant constructs for checking the negative impressions.

For accomplishing the research goals, 11 independent features linked to blockchain architecture and the Bitcoin mining process have been identified to perform predictive modeling. Justifications for using the salient features have been drawn employing the Generalized Mean Information Coefficient (GMIC) and Maximal Information Coefficient (MIC) driven nonlinear association mining techniques. Facebook's Prophet (Taylor and Letham, 2018) and Deep Neural Network (DNN) (Liu et al., 2017) have been deployed to carry out predictive analysis of daily energy consumption and E-waste generation from Bitcoin mining. A comparative study of both methods has been conducted to determine their relative efficiency. We try to understand the nature of E_waste generation and energy consumption at a deeper level by incorporating explainable artificial intelligence (AI). Both Prophet and DNN provide a very narrow interpretation of how the input features drive the adverse impacts of Bitcoin mining. Hence, adding explainable AI into the predictive modeling provides meaningful insights pertinent to curbing the hazardous throughput of Bitcoin mining. We use SHAP and LIME for implementing explainable AI to decode features related to the adverse impacts of Bitcoin mining.

The rest of this paper is oriented next. The literature review is presented in Section 2 Section 3. presents the critical statistical properties of underlying datasets used in the research and fundamental analysis. The utilized research models are elucidated in detail in Section 4 Section 5. presents the results of research models in meeting the research objectives. Subsequently, discussions are presented on critical implications in Section 6. Conclusions are presented in Section 7.

2. Literature review

The potential hazards of excess Bitcoin mining have been mentioned in the literature. For example, Salam and Varma (2019) showed evidence of bacteria with potential bio remediating properties in soil contaminated with electronic waste Mohammadi et al. (2021). used material flow analysis to approximate E_waste generation in Caribbean islands. Their results indicated a steep rise in E_waste that would result in hazardous environmental impacts Jana et al. (2021). used machine learning algorithms for identifying the key determinants of E_waste discharge in Bitcoin mining. However, the said work considered the energy intake as an explanatory feature instead. The underlying work predicts both these constructs separately.

Resmi and Fasila (2017) developed an algorithm for predicting E_waste in refurbishment industries. Numerical simulations demonstrated the accuracy of the framework Duman et al. (2019). developed a nonlinear gray Bernoulli model for estimating E_waste generation in Washington. Overall results suggested the model's utility in managing waste through implementing reverse logistic setup, stringent recycling, and disposal activities Gandara-Perez et al. (2020). conducted empirical research that expounded how waste from electrical and electronic equipment in Colombia's healthcare sector can be managed. The study's findings are extremely useful for practical implementation and strategy formulation for combating waste in the said sector.

Kang et al. (2020) estimated electronic waste collection from Malaysian households using the Internet of Things. The architecture was demonstrated to be highly efficient and intelligent for automation, recycling precious metals from waste, and preserving sustainability Mao et al. (2020). developed fractional gray incorporating exponential kernel for predicting the quantum of electronic waste and precious metal content of it generated in mobile phones, laptops, desktops, and televisions. The model was found to capture the trend of waste generation effectively. The methodological framework of Ilyas et al. (2021) demonstrated procedural steps of mitigating adverse environmental impacts and restoration of precious metals from electronic waste through resorting to the microbial recycling process Wang et al. (2021). proposed a predictive architecture to estimate E_waste from appliances precisely. The efficacy of the proposed framework could be leveraged for developing recycling plans.

The current work uses state-of-the-art AI frameworks to model the E_waste accumulation and energy consumption and identify the key enabler to reduce the hazardous footprints in the Bitcoin mining process. Likewise, E_waste modeling applications of AI have been reported in estimating energy consumption in various sectors (Jana et al., 2020). As a result, we use AI algorithms to model E_waste generation and energy consumption arising from Bitcoin mining. We use Facebook's Prophet and DNN in the endeavor. Facebook's Prophet is an emerging predictive modeling algorithm with growing traction in resolving complex patterns mining problems.

Zhao et al. (2018) leveraged Facebook's Prophet for successfully predicting fluctuations of ambient fine particulate matter concentrations in the United States. The findings revealed insightful patterns related to the periodicity of fine particulate matters concentration Dorokhoba et al. (2020). used Prophet-based predictive modeling for predicting occupancy to manage energy savings through air conditioning devices. The results rationalized the efficacy of the proposed intelligent energy-saving framework. Prophet algorithm has also been used for predicting sales of seasonal items (Ensafi et al., 2021) Guo et al. (2021). developed an integrated forecasting framework utilizing Facebook's Prophet and support vector regression (SVR) for demand forecasting with explicit seasonality. Prophet was used for estimating seasonal fluctuations Saracoglu et al. (2021). developed a framework based on Facebook's Prophet to forecast peak traffic for efficient transportation planning.

On the other hand, DNN has been acknowledged as a relatively more established model for drawing precise predictions in complex research problems (Kumar et al., 2020; Ha and Chen, 2021). It has been successfully used for time series prediction (Abedin et al., 2021; Ghosh and Datta Chaudhuri, 2021). Thus, selecting these two methodologies to resolve the research problem serves methodological insights in the form of a comparative study.

3. Data properties and fundamental analysis

Conceptualization and operationalization of key constructs for measuring E_waste generation and energy consumption are crucial for accomplishing the research goals. This section expounds on the variables and the fundamental statistical properties for subsequent advanced data analysis. Daily data of E_waste generation, energy consumption, and eleven input features over the timespan of February 10, 2017, to July 7, 2020, have been collated from www.quandl.com and www.digiconomist.net. The first website is a leading source of economic and financial data, whereas the second website is a unique source of cryptocurrency-related data.

Following the existing literature (Koutmos, 2018; Das and Dutta, 2019), we identify the variables as explanatory features responsible for energy consumption and E_waste generation: average block size (Average_Blocksize), blockchain size (Bitcoin_Blockchain), cost per transaction (Cost_Per_Transaction), hash rate (Bitcoin_Hashrate), miner revenue (Miner_Revenue), unique address (Unique_Address), transaction fee (Transaction_Fee), transaction per block (Transaction_Per_Block), unique transaction (Unique_Transaction), market price of Bitcoin (Bitcoin_Market_Price), and market capitalization of Bitcoin (Market_Capitilization). Among these selected features, Cost_Per_Transaction, Miner_Revenue, Transaction_Fee, Bitcoin_Market_Price, and Market_Capitilization accounts for the monetary amount involved in the Bitcoin mining process, reward, and market sentiment of Bitcoin. In contrast, the remaining features reflect critical parameters of the blockchain network responsible for hosting the digital currency processing Tables 1. and 2 outline the fundamental properties of underlying variables.

From Table 1, we find that the data corresponding to the variables exhibits leptokurtic distribution. Variables like Market_Capitalization, Blocksize_Blockchain, Hashrate, Unique_Address, and Unique_Transaction demonstrate a high amount of variation as manifested by substantially higher standard deviation values. From Table 2, the outcome of both Shapiro-Wilk and Frosini tests suggests that none of the considered variables follow Gaussian distribution. The outcome of the ADF and Zivot-Andrews (ZA) tests implies that some of these time series are stationary while the remaining are not. Lastly, the estimated Hurst exponent of concerned variables is substantially greater than 0.5, indicating that the series is non-random and driven by persistent patterns. Therefore, clear evidence of non-parametric and fractional behavioral patterns occasionally exhibiting non-stationary traits is apparent. Hence, it would be ideal to rely upon a research framework capable of modeling nonlinear patterns in a non-parametric setup. Thus, advanced predictive modeling and explainable AI to model the daily E_waste generation and the energy consumption is duly justified.

4. Research methodology

The MIC and GMIC have been used to examine the presence of nonlinear nexus. Also, two predictive analysis models - Facebook's Prophet and DNN have been used to predict the future values of E_waste and energy consumption. Facebook's Prophet is an emerging predictive modeling algorithm with remarkable success in modeling time-series observations. In contrast, DNN has been widely regarded as highly efficient in mining complex nonlinear patterns. The performance of both models has been investigated by using various performance indices and statistical tests. Both models are built on chosen explanatory features discussed in the previous section. It may be noted that Prophet or DNN cannot explicitly evaluate the importance and nature of explanatory features in driving the target manifests. Thus, a mere predictive analysis may not be adequate to comprehend how independent drivers can be leveraged to reduce the negative impacts of Bitcoin mining. As a result, we apply explainable AI tools for accomplishing this task. This section presents the methodological components and several performance measures used for validating the findings.

4.1. Nonlinear association delving

Since no significant linear association could be observed. It is imperative to use frameworks capable of detecting other forms of nexus. Two non-parametric statistical indices - MIC and GMIC have been employed to decode the degree of interconnectedness of the chosen explanatory variables with the dependent ones.

4.1.1. The MIC

Reshef et al. (2011) proposed the MIC to detect nonlinear associations. It is a member of the maximal information-based non-parametric exploration (MINE) family. The magnitude of MIC ranges from zero to one. Values close to zero imply a sign of independence, while magnitudes close to one infer a strong bond. For more details on MIC, please see Jana et al. (2021).

4.1.2. The generalized mic (GMIC)

Luedtke and Tran (2013) developed the concepts of GMIC to address a few MIC pitfalls in the presence of noisy data. GMIC can capture the functional/non-functional associations. It lies between zero and one. A blend of MIC and GMIC is sufficient to discover relations created through the superimposition of ordinary functional forms and complicated nonlinear structures.

4.2. Facebook's prophet

It is a predictive modeling algorithm developed by Facebook's core data scientists for solving time series forecasting problems in univariate and multivariate frameworks (Taylor and Letham, 2018). The model is highly efficient in analyzing complex patterns of daily, weekly, monthly, and yearly time intervals by capturing trends, sharp regime shifts, seasonality, holiday effects, etc. The Prophet model's specification can be expressed as follows:

Table 1
Descriptive statistics of underlying variables.

Series	Minimum	Maximum	Mean	Median	Std. Dev.	Skewness	Kurtosis
Average_Blocksize	0.45	1.41	0.996	0.991	0.16	-0.39	0.35
Blocksize_Blockchain	1.02e+05	2.86e+05	1.91e+05	1.88e+05	5.33e+04	0.06	-1.21
Cost_Per_Transaction	6.45	161.69	47.18	45.33	26.96	1.087	1.54
Hashrate	2.92e+06	1.36e+08	4.85e+07	4.30e+07	3.69e+07	0.54	-0.89
Miner_Revenue	1.70e+06	$5.32\ e+07$	1.31e+07	1.25e+07	1.60	4.58	4.57
Unique_Address	3.01e+05	1.07e+06	5.30e+05	5.24e+05	1.04e+05	1.19	2.93
Transaction_Fee	9.97	1495.95	116.97	38.59	155.92	2.76	11.49
Transaction_Per_Block	859.10	2762.54	1911.24	1977.45	399.06	-0.42	-0.64
Unique_Transaction	1.32e+05	4.91e+05	2.82e+05	2.87e+05	5.76e+04	-0.12	-0.41
Bitcoin_Market_Price	956.79	19,498.68	6681.55	6840.24	3202.56	0.28	0.27
Market_Capitalization	1.52e+10	3.27e+11	1.18e+11	1.22e+11	5.76e+10	0.20	-0.07
Energy	3.08	60.09	33.77	41.08	18.05	-0.57	-1.21
E_waste	0.65	12.98	7.23	8.75	3.81	-0.57	-1.15

Table 2
Additional fundamental features of underlying variables.

Series	Shapiro-Wilk Test	Frosini&Test	ADF Test	ZA Test	Hurst&Exponent
Average_Blocksize	0.98***	0.75***	-1.66*	-17.16***	0.73
Blocksize_Blockchain	0.96***	1.18***	16.46#	-29,239#	0.91
Cost_Per_Transaction	0.93***	1.46***	-2.12**	-6.91***	0.81
Hashrate	0.91***	1.99***	-0.41#	-3.26#	0.67
Miner_Revenue	0.89***	1.44***	-1.45#	-3.33#	0.72
Unique_Address	0.93***	1.18***	-1.75*	-15.07***	0.76
Transaction_Fee	0.67***	4.28***	-3.70***	-7.55***	0.83
Transaction_Per_Block	0.97***	1.22***	-1.60#	-2.97#	0.78
Unique_Transaction	0.99***	0.73***	-1.57#	-3.56#	0.76
Bitcoin_Market_Price	0.97***	0.74***	-0.43#	-2.83#	0.89
Market_Capitalization	0.98***	0.76***	-0.35#	-2.76#	0.82
Energy	0.87***	2.73***	0.41#	-2.69#	0.91
E_waste					

*** Significant at 1%, ** Significant at 5%, and * Significant at 10% levels of significance, # Not significant.

$$y(t) = g(t) + s(t) + h(t) + x(t) + \epsilon_t \tag{1}$$

where, $y(t)$ denotes the underlying time series to be predicted, $g(t)$ accounts for the trend component responsible for linear or nonlinear changes, periodic components of different time horizons are represented by $s(t)$, holiday effects due to irregular schedules are represented by $h(t)$, the influence of exogenous constructs are measured through $x(t)$, and finally ϵ_t denotes the residual component.

This study has not considered the holiday effects since Bitcoin trading can hardly depend on the same. On the other hand, eleven explanatory variables have been considered to predict electronic waste and energy consumption. Thus, we can protrude Eq. (1) as:

$$EWaste(t) = g(t) + s(t) + \sum_{i=1}^{11} x(t) + \epsilon_t \tag{2}$$

$$Energy(t) = g(t) + s(t) + \sum_{i=1}^{11} x(t) + \epsilon_t \tag{3}$$

Future figures of both variables are estimated using Eq. (2) and Eq. (3).The Prophet allows linear and logistic functions for modeling the trend component accordingly. We model the growth part using a piecewise constant function that offers highly accurate modeling in this work. Mathematically, the trend part is represented by Eq. (4):

$$g(t) = \left(k + a(t)^T \delta\right)t + \left(m + a(t)^T \gamma\right) \tag{4}$$

Here, k denotes the growth rate, $\delta(\in \mathbb{R}^S)$ is the rate adjustment parameter that allows S change points to be incorporated in the model, m denotes the offset parameter, and γ controls the magnitude of the rate of change. The change points can be manually specified or automatically estimated.

For daily samples, Prophet automatically estimates weekly and yearly seasonality segments. The seasonality is modeled using a Fourier series as shown in Eq. (5):

$$s(t) = \sum_{n=1}^{N} \left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{P}\right)\right) \tag{5}$$

where P denotes the period of the time series (Yearly, Weekly, Daily, etc.). Therefore, modeling seasonality demands computations of 2 N parameters, $\beta = [a_1 b_1 \ldots a_N b_N]^T$. The estimation is achieved through forming a matrix of seasonality vectors for individual values of t, viz. yearly seasonality, and at $N = 10$. Mathematically, it is represented using Eq. (6):

$$X(t) = \left[cos\left(\frac{2\pi(1)t}{365.25}\right), \ldots, sin\left(\frac{2\pi(10)t}{365.25}\right)\right] \tag{6}$$

The seasonal component is expressed using Eq. (7) :

$$s(t) = x(t)\beta \tag{7}$$

where $\beta \sim N(0, \sigma^2)$ is considered for imposing smoothing before seasonality. A smaller N value implies deploying a low pass filter to seasonality, while a higher value enables fitting to highly volatile seasonal patterns.

Prophet can be used to forecast selected test data where the algorithm assumes average frequency and magnitude of trend change remains unaltered. Prophet has been found to be highly robust to outliers, missing data, regime shifts, etc., and found to be successful in complex predictive modeling tasks (Aguilera et al., 2019; Weytjens et al., 2019). To implement Facebook's Prophet algorithm, 'fbprophet' library has been used in the Python programming environment. Additive seasonality components using daily periodic patterns and Fourier order of 30 have been selected for executing the model. Default values of other parameters have been kept that are auto-tuned by the algorithm for the best fit.

4.3. The DNN

ANN with multiple hidden layers is referred to as DNN (Liu et al., 2017). Keeping several layers enables better feature transformation, drastically improving overall results pertinent to complex pattern discovery. Each hidden layer of the DNN consists of several neurons. These neurons obtain outputs from the preceding layer and produce output for the subsequent layer by deploying the activation function.

Neurons weigh the previous layer's output and transfer them to the next layer using the following equations (Eqn 8, 9, 10):

$$x_{k,i} = \sum_{j=1}^{N_{k-1}} \left[\left(w_{k-1,j,i} z_{k-1,j}\right) + b_{k,i}\right] \tag{8}$$

$$z_{k,i} = \frac{1}{1 + e^{-x_{k,i}}} \tag{9}$$

$$Y = \sum_{i=1}^{N_3} w_{3,1,i} Z_{3,i} \tag{10}$$

where Y is the outcome, z is the resulting value obtained from the transformation function, w is the weight, b is the bias unit, $x_{k,i}$ is the i th neuron of hidden layer k, and N_k is the number of neurons of layer k. In this work, we have utilized the DNN in a multivariate framework to estimate electronic waste and energy consumptions of Bitcoin mining. For executing the DNN, we use 'Keras' interface of Python with 50, 40, and 30 hidden nodes in three hidden layers, 'Rectified Linear' activation function in hidden layers, and 'Linear' activation function in the output layer. Also, Adam' algorithm is run for 500 iterations to learn the parameters.

4.4. Explainable AI

The forecasting models used in this study yield a highly accurate prediction for E-waste generation and energy consumption. However, the interpretability of the nature of the influence of explanatory features is missing. We use Explainable AI to interpret operations and the true nature of features at a granular level (Mittelstadt et al., 2019; Rudin, 2019). Several interesting frameworks have been developed under the umbrella of Explainable AI of late. For example, SHAP (Lundberg and Lee, 2017) and LIME (Ribeiro et al., 2016) have been used for explaining the role of selected input features in predicting energy consumption and E_waste generation.

Since the underlying time-series observations of target and exogenous constructs have appeared to be non-parametric and persistent while exhibiting nonlinear association, the deployment of models capable of delving such patterns is essential for drawing final inferences. The ability of Facebook's Prophet, DNN, and explainable AI to deal with non-parametric and nonlinear evolutionary patterns make them suitable for estimating E-waste generation and energy consumption.

4.5. Predictive performance assessment

It is essential to partition the data into training and test segments to perform predictive analysis. We use three settings of training and test samples (80%−20%), (70%−30%), and (60%−40%) to evaluate the predictive performance of Facebook's Prophet and DNN models. We adopt a forward-looking approach for segregating the datasets. For example, in (80%−20%) setup, observations ranging from February 10, 2017, to October 31, 2019, constitute the training segment, while samples from November 1, 2019, to July 7, 2020, constitute the test segment. Similarly, training and test segments are generated for the other two setups. The train and test set generation approaches are more robust in ascertaining the performance of forecasting models.

Three partitions are considered to check and validate both models' capability in executing predictive exercise at different settings. For example, (60%−40%) setting accounts for the extreme conditions reflecting comparatively low training samples for model building and substantially high time horizons for prediction. This setting is equivalent to considering last year's record for developing a model and then using the trained model to estimate the E_waste generation and energy consumption for the next eight months. On the other hand, (80%−20%) setting depicts situations with a substantially high quantum of training samples. Therefore, checking predictive performance in these three settings inspects models' forecasting capability in realistic and practical situations. We use the following four performance indices as represented by Eqn 11, 12, 13, 14 to judge the quality of prediction (Jana and Ghosh, 2022):

(i) Nash-Sutcliffe Efficiency (NSE):

$$NSE = 1 - \frac{\sum_{t=1}^{N}\{\widehat{Y}_t - Y_t\}^2}{\sum_{i=1}^{N}\{Y_t - \overline{Y}_t\}^2} \tag{11}$$

(ii) Index of Agreement (IA):

$$IA = 1 - \frac{\sum_{t=1}^{N}\{\widehat{Y}_t - Y_T\}^2}{\sum_{i=1}^{N}\{|Y_t - \overline{Y}_t| + |Y_t - \overline{Y}_t|\}^2} \tag{12}$$

(iii) Theil Index (TI):

$$TI = \frac{\left[\frac{1}{N}\sum_{t=1}^{N}(\widehat{Y}_t - Y_t)^2\right]^{1/2}}{\left[\frac{1}{N}\sum_{i=1}^{N}(\widehat{Y}_t)^2\right]^{1/2} + \left[\frac{1}{N}\sum_{i=1}^{N}(Y_t)^2\right]^{1/2}} \tag{13}$$

(iv) Directional Predictive Accuracy (DA):

$$DA = \frac{1}{N}\sum_{t=1}^{N} D_t,\ D_t = \begin{cases} 1, & (Y_{t+1} - Y_t)(\widehat{Y}_{t+1} - Y_t) \geq 0 \\ 0, & Otherwise \end{cases} \tag{14}$$

Diebold-Marino (DM) test for equal predictability has been used to statistically compare the predictive performance of Facebook's Prophet and DNN. It is a pairwise test that can detect whether these algorithms' predictions are statistically different or not. Usage of the DM test for evaluating the performance of time series prediction has been previously reported in the literature (Ghosh et al., 2019; Jana et al., 2020).

5. Results

This section presents our results on E_waste generation and energy consumption from Bitcoin mining by detailing nonlinear associations between independent and response variables, outcomes of predictive modeling, and the analysis of explainable AI.

5.1. Outcome of association mining

The *'Minerva'* package of R library has been utilized to determine MIC and GMIC metrics' magnitudes Table 3. presents the MIC and GMIC values that reflect the strength of dependence of any functional form between the target and independent variables.

The results indicate that Blocksize_Blockchain shares the highest bond with energy consumption and E_waste generation as MIC and GMIC values are close to 1. Hashrate and Transaction_Fee also share high dependence on both factors manifested by substantially higher MIC and GMIC values. Unique_Address associated with low MIC and GMIC values has appeared to share relatively low dependence. However, unlike mere linear correlation, MIC and GMIC have been able to discover the presence of nonlinear association. Hence, the inclusion of said features in predictive setups of Facebook's Prophet and DNN is justified.

5.2. Outcome of predictive modeling

The data portioning process enunciated in Section 4.5 has been utilized to expound the accuracy of predictions using the four performance indicators Tables 4, 5, 6 present the predictive performance of Facebook's Prophet and DNN manifested under different training-test

Table 3
MIC and GMIC statistics and input features.

Variables	Energy consumption		E_waste generation	
	MIC	GMIC	MIC	GMIC
Average_Blocksize	0.426	0.373	0.443	0.385
Blocksize_Blockchain	0.999	0.975	0.999	0.974
Cost_Per_Transaction	0.499	0.449	0.498	0.448
Hashrate	0.913	0.899	0.912	0.899
Miner_Revenue	0.468	0.440	0.461	0.439
Unique_Address	0.319	0.248	0.324	0.254
Transaction_Fee	0.717	0.698	0.719	0.699
Transaction_Per_Block	0.399	0.328	0.409	0.337
Unique_Transaction	0.394	0.318	0.409	0.329
Bitcoin_Market_Price	0.568	0.542	0.568	0.5425
Market_Capitilization	0.563	0.543	0.563	0.543

Table 4
Performance of Prophet and DNN on (80%−20%) setting.

	Energy Consumption Prediction (Prophet)	Energy Consumption Prediction (DNN)	E_waste Generation Prediction (Prophet)	E_waste P Generation rediction (DNN)
Training Dataset				
NSE	0.997	0.999	0.997	0.999
TI	0.001	0.000	0.001	0.001
IA	0.997	0.999	0.997	0.999
DA	0.994	0.998	0.994	0.998
Test Dataset				
NSE	0.995	0.998	0.995	0.998
TI	0.002	0.001	0.002	0.001
IA	0.996	0.998	0.995	0.998
DA	0.984	0.992	0.984	0.992

Table 5
Performance of Prophet and DNN on (70%−30%) setting.

	Energy Consumption Prediction (Prophet)	Energy Consumption Prediction (DNN)	E_waste Generation Prediction (Prophet)	E_waste Generation Prediction (DNN)
Training Dataset				
NSE	0.995	0.998	0.995	0.998
TI	0.001	0.007	0.001	0.001
IA	0.995	0.999	0.995	0.999
DA	0.992	0.995	0.992	0.995
Test Dataset				
NSE	0.993	0.997	0.992	0.997
TI	0.002	0.002	0.004	0.002
IA	0.993	0.997	0.993	0.997
DA	0.987	0.989	0.987	0.989

Table 6
Performance of Prophet and DNN on (60%−40%) setting.

	Energy Consumption Prediction (Prophet)	Energy Consumption Prediction (DNN)	E_waste Generation Prediction (Prophet)	E_waste Generation Prediction (DNN)
Training Dataset				
NSE	0.984	0.991	0.983	0.990
TI	0.002	0.002	0.003	0.002
IA	0.985	0.992	0.990	0.991
DA	0.981	0.988	0.981	0.988
Test Dataset				
NSE	0.980	0.989	0.98	0.988
TI	0.010	0.008	0.012	0.009
IA	0.981	0.989	0.988	0.989
DA	0.976	0.984	0.976	0.984

partitions.

From Table 4, we notice that the NSE and IA values are more than 0.99 on both training and test samples for both predictive frameworks. On the other hand, TI values are very low. The training and test segments predictions are linked to substantially higher NSE and IA values and significantly low TI values. Therefore, both Prophet and DNN models can be classified as highly efficient predictive models that use the identified set of features in a multivariate framework. The DA values, reflecting the capability of both models in accurately estimating the trends are close to 1 on training and test segments. High values of DA metrics suggest both the techniques can accurately predict the rise and fall of E_waste generation and energy consumption in the future. Therefore, the overall quality of predictions by Prophet and DNN models in the (80%−20%) setting is the best.

The performance of both Prophet and DNN is like the earlier set up in the (70%−30%) setting. NSE and IA values are close to 1, and TI values are close to 0, justifying the deployment of proposed models in estimating the two target outcomes. The DA values are also substantially high on both training and test segments. Therefore, both the predictive models are efficient in accurately forecasting future movements.

The third segment (60%−40%) setup reflects the extreme conditions when the presence of training samples is not significantly adequate. The NSE and IA values have seen a marginal dip, while TI values have seen a slight increase on both training and test segments. Similarly, DA values have appeared to be comparatively lower than the previous two settings. Therefore, the prediction accuracy in the (60%−40%) setup is not as precise as in the other two segments. The said phenomenon is expected considering the reduction of training samples. However, the overall predictive performance of Facebook's Prophet and DNN is highly acceptable, as apparent from the respective performance measures. Hence, both frameworks can effectively be used for drawing accurate forecasts of E_waste generation and energy consumption in the conventional Bitcoin mining process, even in the absence of adequate training data. The propounded frameworks can be leveraged for projecting future figures and trends with a commendable degree of efficacy. The performance is very encouraging in framing policies, opting for different mechanisms for controlling adverse implications of Bitcoin mining.

5.3. Outcome of comparative performance assessment

The DM test results presented in Tables 7,8 compare the performance of Prophet and DNN on training and test data segments explicitly. A positively significant test statistic value indicates that the column's model outperforms the model arranged in a row. A negatively significant test statistic indicates the reverse consequence, i.e., the model in a row is statistically superior to the model in the column. Insignificant test statistic values indicate no significant difference in performance.

From Table 7, we observe that the performance of the DNN is marginally better than the Prophet algorithm in terms of prediction accuracy, as apparent from the sign and significance level of the test statistics. A comparative analysis on both training and test segments reveals a similar finding. Therefore, the accuracy of futuristic projections of energy consumption by DNN in Bitcoin mining is marginally superior to the Prophet algorithm. However, the quality of Prophet-based prediction is no way near to be classified as poor quality by any means, as apparent from the values of performance indicators outlined in Tables 4-6.

From Table 8, we find that the predictive performance of E_waste generation in the Bitcoin mining on training and test segments is like that of energy consumption modeling. The DNN has emerged to be marginally better than the Prophet-based framework.

Hence, the overall outcome of DM tests suggests the supremacy of DNN over Facebook's Prophet in yielding energy consumption and

Table 7
The outcome of the DM test for energy consumption prediction.

Models	Prophet (80%−20%)	Prophet (70%−30%)	Prophet (60%−40%)
		Training Set	
DNN (80%−20%)	3.37***		
DNN (70%−30%)	–	3.42***	
DNN (60%−40%)	–	–	3.57***
		Test Set	
DNN (80%−20%)	3.76***		
DNN (70%−30%)	–	3.95***	
DNN (60%−40%)	–	–	4.13***

*** Significant at 1% level of significance.

Table 8
The outcome of the DM test for E_waste generation prediction.

Models	Prophet (80%−20%)	Prophet (70%−30%)	Prophet (60%−40%)
		Training Set	
DNN (80%−20%)	3.26***		
DNN (70%−30%)	–	3.29***	
DNN (60%−40%)	–	–	3.42***
		Test Set	
DNN (80%−20%)	3.74***		
DNN (70%−30%)	–	3.91***	
DNN (60%−40%)	–	–	4.08***

*** Significant at 1% level of significance.

E_waste generation forecasts of Bitcoin mining in the blockchain network. However, it may be noted that the difference is marginal as the Prophet algorithm also results in forecasts of reasonable accuracy. Above that, Prophet requires a minimal number of parameters to be specified explicitly beforehand compared to DNN. Thus, Prophet is an attractive option for predictive analysis in a real-time environment. In brevity, a rigorous comparative exploration of the execution time, memory requirement, and performance accuracy in the future can be a fairer approach to judge the relative efficacy of both frameworks Figs. 1-4. exhibit the performance of Facebook's Prophet algorithm on training and test samples of (80%−20%) set up.

5.4. The outcome of explainable AI driven analysis

As an endeavor of this research, we comprehend the influence of all selected parameters pertinent to blockchain operations and Bitcoin market sentiments from a global and local perspective. SHAP and LIME techniques of explainable AI framework have been applied for accomplishing the tasks. SHAP is used explicitly for gaging the overall importance of respective features in predicting the energy consumption and E_waste generation initially. Subsequently, LIME provides a clear interpretation of the nature of the impact, i.e., positive or negative, at the local level Figs. 5,6. depict the outcome of the investigation through the lens of SHAP.

We find that Blocksize_Blockchain, Transaction_Fee, and Hashrate are the top three contributors to energy consumption and E_waste generation. Therefore, stringent monitoring of these factors becomes consequent imperatives for reducing the negative externalities of Bitcoin mining. On the contrary, Average_Blocksize, Unique_Address, and Unique_Transaction are the least contributory features. We notice that the influence scores of selected features are similar across energy consumption and E_waste generation. Therefore, actions to combat the surge in energy consumption would automatically tame E_waste generation and vice versa. Next, we decode the influence structure locally through the LIME tool. LIME operates at a finer granule. Hence, LIME has been performed on three randomly chosen samples to clarify the influence directions for energy consumption and E_waste generation Figs. 7,8. exhibit the outcome of the LIME driven analysis.

In Figs. 7,8, green bars imply a positive influence, and Red bars imply a negative influence. Features corresponding to no bar show no significant impact on that particular data sample. Features corresponding to Green bars suggest that higher values would result in higher throughput of energy consumption and E_waste generation. In contrast, higher values of the features marked by Red bars would decrease the adverse signs. The results are specific to samples explicitly, i.e., specific to date in the context of the research problem. Blocksize_Bitcoin positively influences both energy consumption and E_waste generation maximally on all chosen samples. Thus, the outcome of local level inspection conforms to SHAP findings that specify Blocksize_Bitcoin is the most prominent feature. Redesign of block sizes should be considered seriously to tackle the enormous energy consumption and E_waste generation from the blockchain network., Transaction_Fee also has the potential to inhibit contagious effects. Thus, policies to increase the charges of transactions may turn out to be a game-changer in tackling the Achilles hills of Bitcoin mining in the blockchain network. It is possible to extend the LIME methodology to more samples to check whether the sign of the impact of considered features stays uniform or varies across different time horizons. Incorporating explainable AI in conjunction with predictive analytics tools provides significant actionable insights that can provide the roadmap to block the blockchain's bottlenecks effectually.

The outcome of nonlinear association mining and predictive modeling indicate the predictable nature of daily E_waste generation and energy consumption from the Bitcoin mining hosted in the blockchain network. Through explainable AI-driven investigations, we have explored the nature of the influence of several key input features at a deeper level of practical relevance for combating blockchain's growing concerns for sustainability. The subsequent section further elaborates on that.

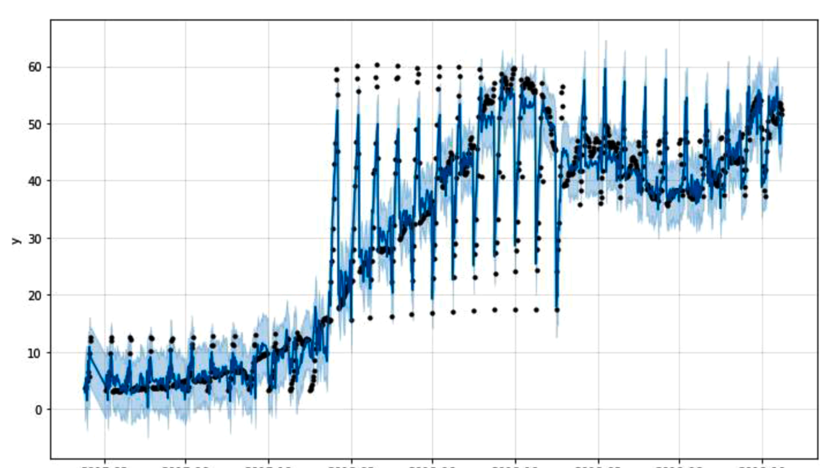

Fig. 1. Performance of Prophet of energy consumption prediction on training samples.

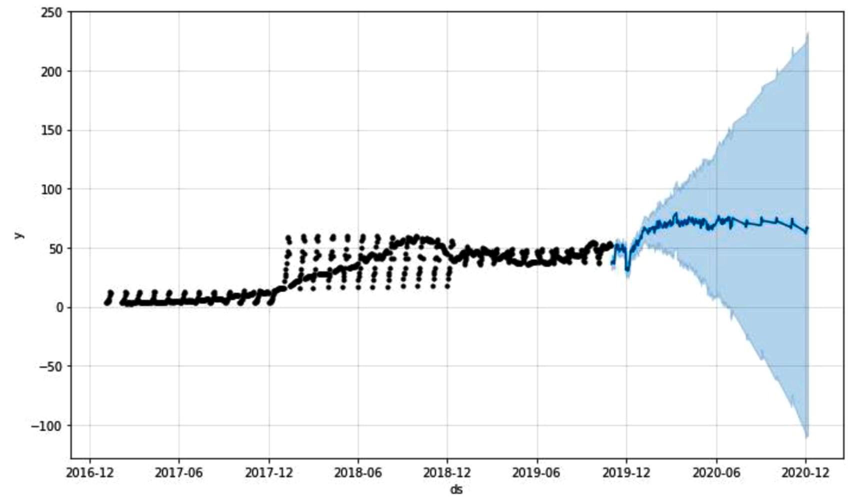

Fig. 2. Performance of Prophet of energy consumption prediction on test samples.

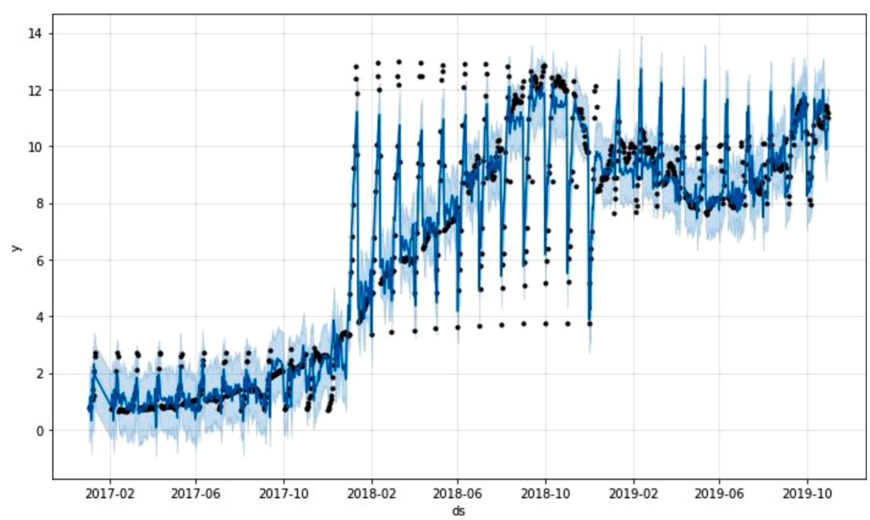

Fig. 3. Performance of Prophet of E_waste generation prediction on training samples.

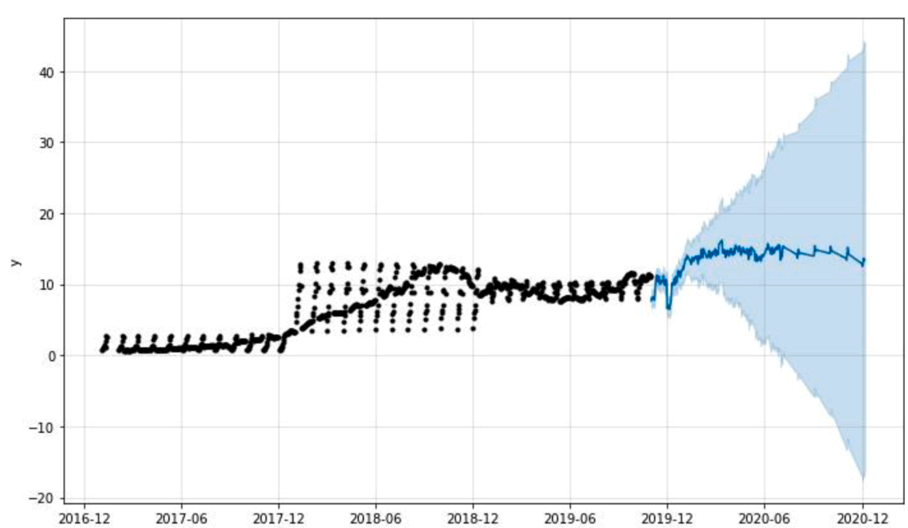

Fig. 4. Performance of Prophet of E_waste generation prediction on test samples.

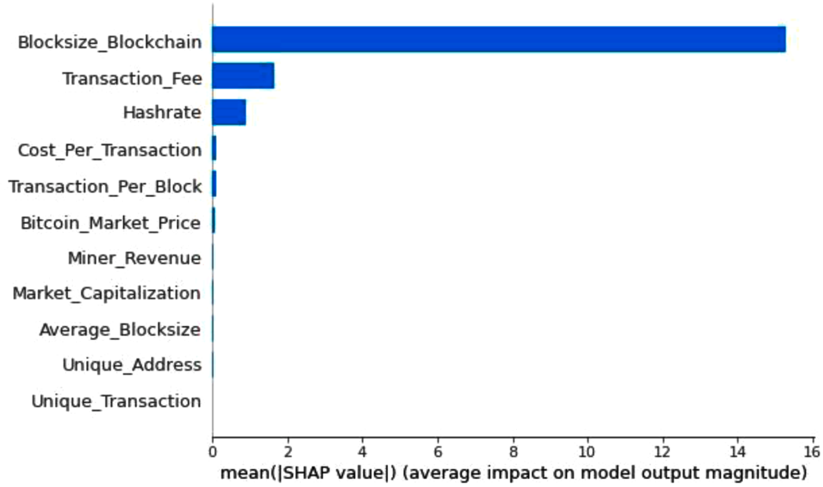

Fig. 5. The output of SHAP inspection of energy consumption modeling.

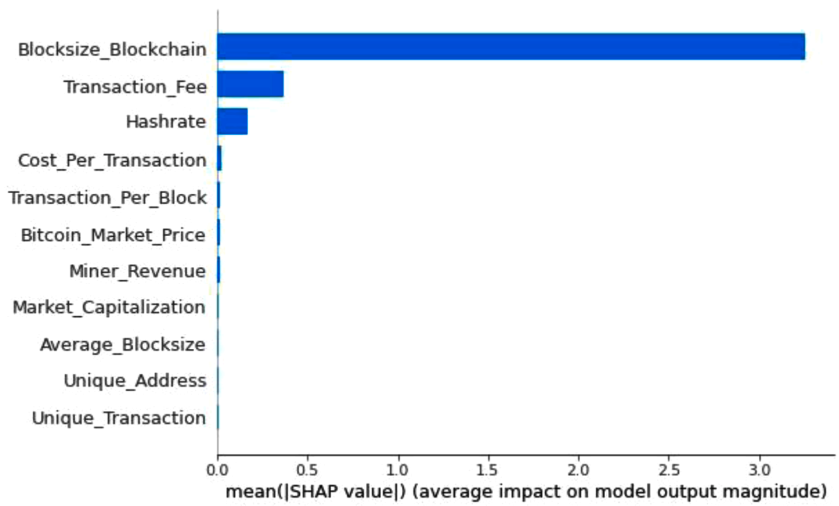

Fig. 6. The output of SHAP inspection of E_waste generation modeling.

6. Discussion and conclusion

6.1. Empirical contribution

We set out to model the adverse effects of Bitcoin mining in terms of energy consumption and E_waste generation. The proposed framework and applying Facebook's Prophet algorithm and deep neural network (DNN) proved to be exceptionally proficient in modeling energy consumption and E_waste generation. Additionally, we relied on two newly developed explainable AI approaches, SHAP and LIME, to examine the influence of key input variables that can regulate energy consumption E_waste generation.

The daily E_waste generation and energy consumption were found to be completely non-parametric and non-stationary. The existence of fractional Brownian motion entrenched in the temporal movements of these two variables is apparent. The relationships between the chosen independent features and output constructs are strongly nonlinear. Nonlinear association mining justified the deployment of advanced modeling for a deeper analysis. Blocksize_Blockchain shares the strongest nonlinear bond with energy consumption and E_waste generation beforehand that have been validated later in the investigation.

Both Facebook's Prophet and DNN are exceedingly effective in predicting energy consumption and E_waste generation. Empirical investigations indicate marginally better performance of DNN compared to Facebook's Prophet in performing predictive exercises. However, Facebook's Prophet is computationally much less complex compared to DNN. A deeper inspection through the explainable AI framework using SHAP and LIME for interpreting “black box” operational processes of deployed advanced predictive algorithms provided insights helpful in developing strategies to curb the adverse effects of Bitcoin mining in the blockchain network. Specifically, we found that Blocksize_Blockchain, Transaction_Fee, and Hashrate are the top three features with the highest explanatory capability, while Average_Blocksize, Unique_Address, and Unique_Transaction are the least significant features. Blocksize_Blockchain acts as a catalyst for the growth in energy consumption and E_waste generation, whereas Transaction_Fee negatively affects the target variables.

6.2. Insights for taming energy consumption and E_waste generation

The overall predictive modeling and explainable AI findings bring out several interesting and actionable insights that can be used to tame energy consumption and E_waste generation. The present research expounds on the severe adversarial effects of intense Bitcoin mining, leading to potentially catastrophic environmental impacts.

Our research has demonstrated that deploying Facebook's Prophet, DNN, and explainable AI is efficacious in decoding the nexus of key parameters reflecting blockchain microstructures and sentiments of

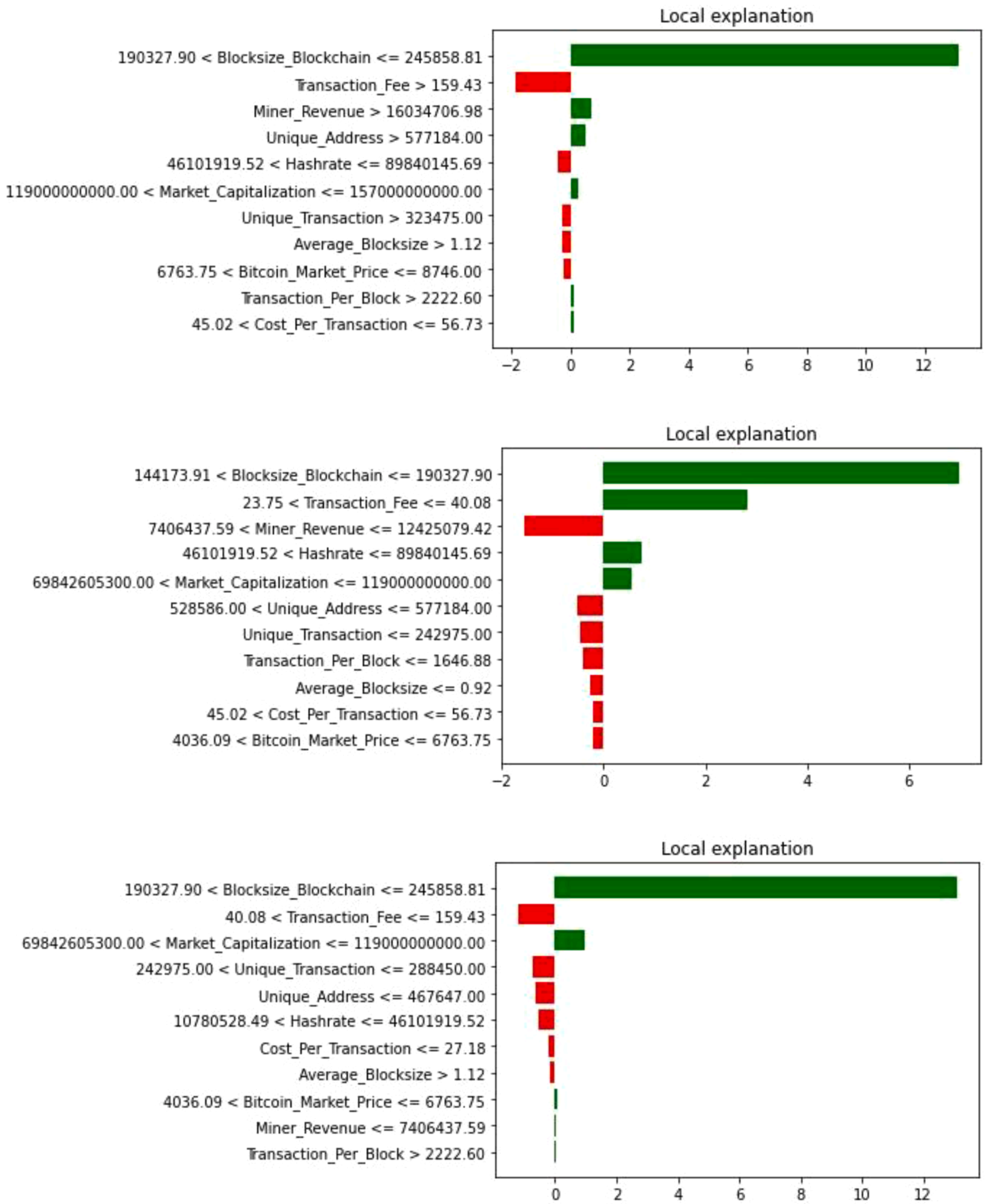

Fig. 7. The direction of effects of chosen features on energy consumption.

Bitcoin markets regarding energy consumption and E_waste generation. This research's findings have demonstrated that future E_waste generation and energy consumption trends can indeed be modeled and efficiently predicted. Explainable AI, in turn, caters to deeper insights on the influence structure of the considered variables linked to the mining process in the blockchain network on E_waste generation and energy consumption. This may help develop actionable measures to reduce the adverse impacts of Bitcoin mining.

Blocksize_Blockchain was the factor with the highest contribution to E_waste generation and energy consumption. Transaction_Fee and Hashrate are the second and third most important features in terms of explanatory capability. We also explore whether the features positively or negatively affect the outcome at a granular level. It is essential to analyze these features as the adverse effects can be effectively controlled if these factors are monitored. This research's explainable AI component helps us identify and measure the features responsible for E_waste generation and energy consumption.

Further, it provides the strength of the influence of the said features. The explainable AI outcome implies that the transaction fee negatively affects E_waste generation and energy consumption, while the miner's revenue exhibits a reverse interplay. This will directly impact the Bitcoin miners to migrate to a newer mining structure and sacrifice revenue. The findings suggest a smaller block size could reduce the overall energy consumption and E_waste generation. In addition, Transaction_Fee is negatively associated with the two bottlenecks, and therefore an increase in transaction charges can minimize the blockchain traffic and

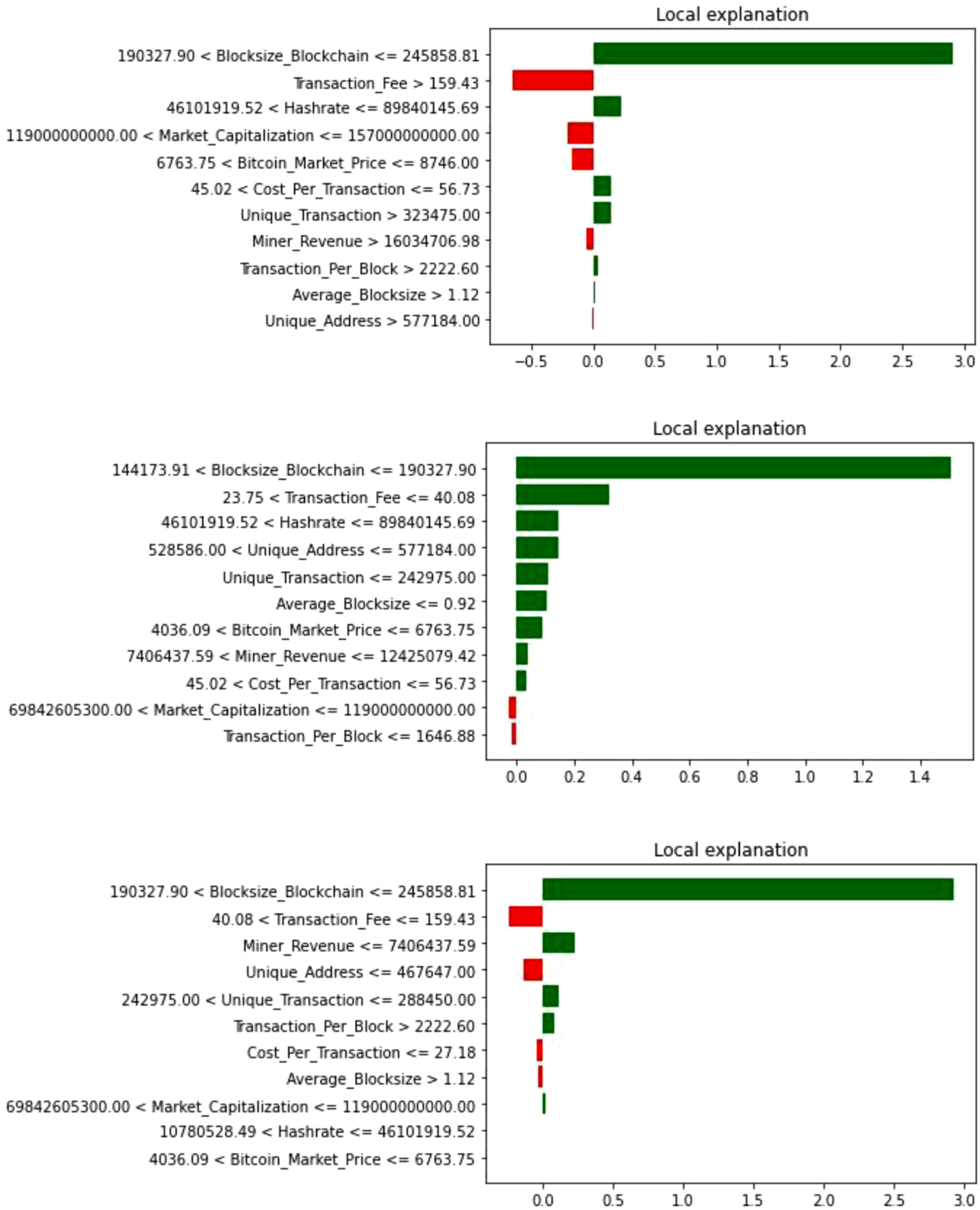

Fig. 8. The direction of effects of chosen features on E_waste generation.

effectively regulate the hazardous environmental footprint.

Replacing the traditional Proof-of-Work (PoW) algorithm by Proof-of-Stake (PoS) technique has been proposed for reducing the rate of energy consumption (Li et al., 2019). PoS is used for preserving network consensus (Bentov et al., 2014). The said framework demands validators to give way all Bitcoins to the network after the engagement initially. Illicit transactions would fetch all Bitcoins. The recorded time and archived Bitcoins would eventually select validators to be rewarded for the validation work. PoS has been proven to be substantially less resource-intensive. This alternative structure can be tested to measure whether significant improvement can be achieved in taming the negative throughput. PoS (DPoS) and some of its variants are delegated as different promising protocols (Yang et al., 2019) can be explored as well. Subsequently, either Prophet or DNN algorithmic structures can estimate the energy consumption and E_waste generation for PoS, DPoS, and other pertinent protocols in the future to assess the viability. Quest for the development of sophisticated hardware systems that can continue to be highly efficient yet less resource-hungry should continue as well. Recycling electronic waste needs serious attention for revamping to form a viable alternative to address the E_waste generation issue. Thus, the continuous technological innovation and development to propound alternative frameworks for Bitcoin mining can substantially reduce the hazardous effects without affecting the fundamental protocols and properties.

Parallel to technological innovations and developments, framing strategies and policies can help mitigate the problems. Stringent implementation of strict regulations and fiscal policies can prevent the exponential rise of E-waste generation and energy consumption in the future. Charging tax on revenue can significantly confine some miners from repeat participation in the blockchain network would eventually be a viable option for blocking the adverse effects. It may be noted that the surge in carbon footprint owing to the said Bitcoin mining is highly alarming that indeed requires immediate preventive actions globally as we are committed to mitigating the risks for sustainability.

6.3. Limitations and future actions

The present study's scope is restricted in identifying key determinants responsible for E_Waste generation and energy consumption of the Bitcoin mining process at a granular level through the conjunction of applied predictive modeling and explainable AI. This research does not directly propose an alternative, less resource-intensive trading. Also, it is restricted to data samples generated under the PoW scheme in the blockchain. The proposed framework can be extended and simulated under the upcoming and hypothesized protocols designed for less resource-intensive protocols to gage practical viability. The nature of explanatory features' influence evolves with weekly, monthly, and quarterly periods that can be inspected extensively in the future. On the methodological front, the current research compares the prediction accuracy of Facebook's Prophet and DNN models to gage the relative efficiency. It would be fairer to incorporate the factors pertinent to computational expenses to judge the same, as striving for higher accuracy may increase complexity and computational time. A multi-criteria decision-making framework-based approach can be leveraged to accomplish the task that would reveal deeper insights of paramount practical implications in real-life implementation and monitoring., , , ,

Author contributions

R.K. Jana: Conceptualization, Validation, Visualization, Resources, Writing- Original draft preparation. **Indranil Ghosh**: Data curation, Methodology, Software, Validation, Investigation, Writing- Original draft preparation.**Martin W. Wallin**: Writing- Reviewing and Editing, Validation, Supervision.

Declarations of Competing Interest

none.

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