We differentiate *multilayer perceptrons*, *recurrent neural networks*, *regression-based* models, *support vector machines*, and *tree-based* models.

Multilayer perceptrons represent a type of feedforward neural network and consist of one input layer, one or more hidden layers, and one output layer [14, 15]. In feedforward networks, information only flows into one direction. *Multilayer perceptrons* with a non-linear and differentiable activation function can approximate any non-linear function, rendering them universal approximators [22]. Eight of the reviewed papers use *multilayer perceptrons*.

Recurrent neural networks drop the requirement for acyclic graphs from *multilayer perceptrons*, allowing for arbitrary feedback connections of the network [23]. Hammer [16] shows that *recurrent neural networks* with a sufficient number of hidden nodes and non-linear activation function also satisfy the requirements of a universal approximator. Ten papers use *recurrent neural networks*, and they remain the best reported model in all papers that use benchmarked scenarios.

Regression-based models refer to models based on linear regressions (e.g., logistic regressions, lasso regressions, and vector autoregressions). 16 papers employ regression-based models, which often serve as a reference point for more sophisticated machine learning methods.

The underlying idea of *support vector machines* consists of minimizing generalization error through constructing a (set of) hyperplane(s) in a high-dimensional space [17, 24, 25]. Six of the reviewed publications employ *support vector machines*.

Last, seven papers employ *tree-based models*. In these models, the outcomes are cuboid regions with axis-aligned edges [26]. A frequently used implementation of the methodology is the random forest, which constitutes an ensemble of imperfectly correlated trees to reduce the variance of forecasts [18].

Eleven papers employ methods that are part of none of the five major categories (e.g., fuzzy-systems [27]).

3.2 Return-predictive Features

Literature on bitcoin pricing via machine learning uses a multiplicity of return predictive signals. While, for instance, technical features (e.g., historical returns) are used in the literature on pricing traditional financial assets [28, 29], blockchain-based features (e.g., mining difficulty) are specifically related to cryptocurrencies — in particular bitcoin. Unlike stocks, bonds or other financial assets, bitcoins exhibit no fundamental value in a typical sense as they do not promise future cash flows, are not backed by a central bank, and cannot be utilized physically. Due to these different characteristics of bitcoin, it is not possible to use the same feature categorizations as for other financial assets. Based on the reviewed literature, we categorize return predictive features into *technical*, *blockchain-based*, *sentiment-* and *interest-based*, and *asset-based*.

Technical features include past data of the bitcoin market, for instance, historical prices or trading volumes. *Technical* features are the most frequently used features in the reviewed literature (27 models).

Blockchain-based features refer to data from the Bitcoin blockchain, for instance, mining difficulty or the number of transactions per block. Nine papers use *blockchain-based* features.

Sentiment- and interest-based features relate to social media sentiment and internet search volume, for instance, twitter sentiment or google trends data. Ten papers employ this type of feature.

Asset-based features relate to prices and returns of commodities and financial assets other than bitcoin, for instance, oil or stock market prices. *Asset-based* features are used in nine papers.

Features not covered by one of the presented categories are categorized as *other* features. Among these, Demir et al. [30] use economic policy uncertainty, Aysan et al. [31] use geopolitical risks, Hotz-Behofsits et al. [32] use GPU prices from Amazon's bestseller lists. Phaladisailoed and Numnonda [33], as well as Mallqui and Fernandes [34], use timestamps. Demir et al. [30] and Aysan et al. [31] conclude that bitcoin may serve as a hedge against policy uncertainty and geopolitical risks, respectively.

3.3 Prediction Interval

The authors in the reviewed literature use different prediction intervals to price bitcoin. The term "prediction interval" thereby denotes the frequency at which a model makes new predictions. The prediction intervals in the reviewed literature range from five seconds up to one week. Based on the prediction intervals, we group the models into five categories — *second*, *minute*, *hour*, *day*, and *week*.

Second includes models with prediction intervals of less than a minute (3 papers), *minute* between a minute and less than an hour (5 papers), *hour* between one hour and less than a day (3 papers), *day* between one day and less than one week (26 papers), and *week* includes models with prediction intervals of one week or longer (1 paper). Smuts [35] tests multiple models with prediction intervals ranging from one hour to one week and finds that the model with the highest prediction accuracy for bitcoin prices has a prediction accuracy of one week. Madan et al. [36] directly compare prediction intervals of ten seconds and ten minutes and find a slightly higher prediction accuracy for the prediction interval of ten minutes.

3.4 Prediction Types

There are several options to set up the prediction problem for bitcoin pricing. First, we distinguish between prediction problems formulated as a *regression* or *classification* problem. Bitcoin prices and returns are numerical and continuous variables. Hence, it is possible to formulate a *regression* model, which tries to predict the exact values of these target variables. However, one can reduce the *regression* problem into a *classification* problem by creating classes based on the target variable. In this case, the prediction model attempts to predict class affiliations based. Second, we distinguish the literature based on whether *absolute* bitcoin price levels or *relative* price changes are predicted. Traditional financial literature on other financial assets (e.g., on stocks [13]) usually analyzes *relative* price changes.

The reviewed literature formulates the bitcoin pricing problem 14 times as a *classification* problem in and 21 times as a *regression* problem. Some scholars create multiple models and set up the prediction problem as both a *classification* problem and a *regression* problem [34, 37]. For *classification* problems, nine of 14 cases formulate it as a binary *classification* problem, predicting the sign (i.e., positive or negative) of the bitcoin price change. In contrast, three papers split the bitcoin price change into three classes (i.e., positive, neutral, negative). Beyond that, Nakano et al. [38] create four target classes based on the price change quantiles, and Huang et al. [39] create 21 classes based on different bitcoin return intervals. All papers that use *classification* models create target classes based on *relative* price changes, while 17 of the 21 papers that use *regression* models predict *absolute* bitcoin price levels and only four of these papers predict *relative* price changes.

4 Discussion

Overall, the research on bitcoin pricing via machine learning is not at a mature state yet. This may be due to the novelty of the protocol itself [1], and that machine learning techniques require a substantial amount of data to learn relationships between features and target variables. An explicit limitation of the reviewed work is that none of the papers is published in a top-rated finance or information systems journal [40]. Furthermore, a considerable amount of available literature barely meets academic standards in terms of transparent documentation of applied method and results. This includes, for instance, studies reporting unlikely R^2 values for four different methods within the range of .991 and .992 [33]. An R^2 of this magnitude is fairly unusual compared to the rest of the reviewed literature and might indicate setup problems (e.g., the use of unlagged features or a high similarity between features and target). In so, further shortcomings in the documentation render it impossible to reproduce and verify the empirical analyses at all. These include, not explicitly reporting the analyzed time range [41, 42], data split [43], or machine learning setup (e.g., layer structure, activation function, loss function, learning function) [44–46]. Furthermore, inconsistencies in the reporting prohibit reproducing the empirical tests. These inconsistencies can stem from reporting to optimize the number of units in a hidden layer of a multilayer perceptron within a specific range and using a number outside of that range in the final model [47] or setting up a regression problem, but using the accuracy metric for model evaluation without further explanation [48].

Throughout the literature, the machine learning models are built and evaluated on rather short time periods and small data samples. A choice of longer prediction intervals, (e.g. weekly intervals [35]) in combination with advanced machine learning models and a large number of features might result in an insufficient number of data points in the sample [49]. Furthermore, test splits of three percent or less, corresponding to 60 observations or less, limit the generalizability of the reported results [41, 46].

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4.1 Theoretical Implications

Researchers apply a wide variety of methods and underlying architectures with alternating success, such as *artificial neural networks*, *recurrent neural networks*, *regressions-based* models, *tree-based* methods, and *support vector machines*. Their main objectives are accurately predicting the bitcoin price (absolute or relative) using *classification* and *regression* approaches. The models embody a broad spectrum of features, which relate to *technical*, *blockchain-based*, *sentiment- and interest-based*, and *assets-based* aspects. Most researchers use *technical* features for their models. Only few authors [50–52] use features from all four categories. Since 2017, scholars begin to consider features beyond these main categories (e.g., economic policy uncertainty [30]).

Researchers formulate *regression* and *classification* problems equally often until the end of 2017, while from 2018 onwards there is a slight shift towards a higher share of *regression* problems. Consequently, researchers in the field mostly (i.e., 60%) utilize *regression-based* methods in total.

The majority (i.e., 79%) of models are set up with *daily* prediction intervals. The relative share of these *daily* models further increased after 2017. However, varying time horizons and model specifications limited the comparability of methods *across* different papers. Importantly, this resonates with limited options to validate any trading strategies applied. To ensure a certain level of comparability (e.g., uniform time horizons), we focus on comparisons of different methods *within* the same paper. Nevertheless, as they are based on several assumptions (e.g., representative time windows and equally optimal tuning states of different models), these comparisons are limited. None of the authors have published their machine learning model, which would allow future researchers to train the model on new data and compare the performance to other methods. Additionally, there are no widely established guidelines or best practices in this research stream for reporting machine learning models.

Given these limitations, we find that recurrent neural networks, and in particular long-short term memory neural networks, perform well in the bitcoin pricing problem compared to other methods [33, 34, 43–46, 53]. Interestingly, even though long short-term memory neural networks were published in 1997 already [54], the first paper [53] taking these into account is from 2018.

4.2 Practical Implications

Based on the finding that complex network architectures such as recurrent neural networks yield promising results [33, 34, 43–46, 53], future research should evaluate further sophisticated network architectures for this particular problem. This may include assessing the effectiveness of ordinary convolutional neural networks [55], as well as dilated convolutional neural networks [56]. The latter has proven to provide promising results in forecasting S&P 500 stock market index already [57]. However, more sophisticated models require more data [49], which might be achieved, for instance, by considering shorter prediction intervals.

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Beyond identifying appropriate modeling architecture, the process of model reporting demands for refinement and harmonization. Contrasting research from (bio)medical research [58] or psychology [59], the analyzed research follows no established guidelines for uniformly reporting machine learning results. We recommend the following reporting standards for future research in the field of bitcoin pricing via machine learning and machine learning projects in general. First, we propose that researchers are required to reveal and document the entire model configuration (i.e., hyperparameters) in a structured manner. This may include a distinct table providing information about the number of a multilayer perceptron's hidden layers, number of units per layer, activation/loss functions, or optimizers. Second, we propose that researchers publish all reported models and data to enhance the comparability amongst them. Thereby, future scholars may fall back on previously validated modeling approaches. Since all major machine learning frameworks (e.g., TensorFlow, Keras, PyTorch) provide distinct functions to save and export trained models, we argue that publishing model and data to an open research repository (e.g., CORE [60], Open Research Library ANU [61]) is a reasonable and necessary step to ensure a sufficient level of transparency. Third, we propose that researchers who publish new modeling approaches, benchmark their models against other existing and published models from the field on the same dataset. Currently, there is no established benchmarking dataset. However, researchers commonly use benchmarking datasets (e.g., MNIST for handwritten digits) in other machine learning fields. Overall, the guidelines were developed due to shortcomings in the existing bitcoin pricing literature and are therefore of particular importance in this specific field. However, they are applicable to empirical machine learning studies of various domains.

4.3 Limitations

There are three main limitations of the presented analysis. First, machine learning and bitcoin pricing are two fast-evolving research disciplines. Therefore, our work reflects a quick blink in time of the literature in this field, and future analysis may yield different results. Moreover, the scope of our literature search is limited, as there exists no unique and widespread acceptance of the term "machine learning." Additionally, this review suffers from the low quality (insufficient documentation and data samples) from part of the bitcoin pricing literature. Furthermore, we may speculate about the existence of more accurate machine learning models, which are exploited monetarily rather than contributed to the scientific body of literature.

4.4 Future Research

We encourage future researchers in the field to evaluate advanced machine learning models (e.g., dilated convolutional neural networks [56]) for time series forecasting, which are not considered by contemporary research in this field. Theoretical economic models for bitcoin prices [6–9] might help to guide the search for further predictive features. To enable and accelerate scientific progress in the field, we propose that future researchers report all model configurations in a structured way, report and publish their model and data, and benchmark new models against other reported models.

5 Conclusion

Bitcoin has received a considerable amount of interest from researchers and investors since its inception in 2008. The research on bitcoin pricing via machine learning constitutes a relevant and emerging topic. We review the existing body of literature of this research branch based on the guidelines of Webster and Watson [20] and vom Brocke et al. [21]. We structure and analyze the body of literature according to four different concepts, namely *method*, *feature*, *prediction interval*, and *prediction type*. A comparison of methods *within* the same paper indicates that *recurrent neural networks* might be well suited for the prediction problem. Most researchers use features from four categories, namely *technical*, *blockchain-based*, *sentiment- and interest-based*, and *asset-based*. Across the reviewed literature, we find a lack of transparency and comparability, limiting options to validate and reproduce model results and eventually applied trading strategies.

Based on these issues we propose that future researchers (i) reveal all relevant model configurations in a structured way, (ii) publish and upload their model and data to an open research repository, and (iii) benchmark their model against other published models.

Appendix

Table 2. Literature overview. Best method marked with bold cross (based on accuracy or lowest error). For papers using classification and regression: ^{A}: best method for the classification problem, ^{B}: best method for the regression problem. For papers in which an ensemble consisting of multiple methods achieves the best results: ^{C}: methods applied.

	Method						**Features**					**Interval**	**Type**	
Source	Multilayer Perceptrons	Recurrent Neural Networks	Regression-based	Support Vector	Tree-based	Other	Technical	Blockchain-based	Sentiment-/ interest-based	Asset-based	Other	S: Secondly, M: Minutely, H: Hourly, D: Daily, W: Weekly,	Classification	Regression
[47]	×						×					D	×	
[62]			×		**×**	×	×					S	×	
[41]	×					**×**	×					D		×
[31]			×								×	D		×
[63]		×					×		×			M, D		×

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[51]			×				×	×	×	×		D		×
[30]			×				×				×	D		×
[52]			×				×	×	×	×		D		×
[64]			×				×			×		D		×
[37]	×[A]		×[B]	×			×	×				H	×	×
[65]			×		×	×	×					M	×	
[32]						×			×	×	×	D		×
[39]					×		×					D	×	
[66]			×						×			H		×
[67]	×		×	×			×	×		×		D		×
[46]		×	×				×					D		×
[44]		×				×	×					D		×
[68]						×	×		×			D	×	
[45]	×	×					×					D		×
[36]				×	×	×	×	×				S, M, D	×	
[34]	×	×[A]		×[B]	×[A]	×	×	×		×	×	D	×	×
[53]		×	×				×	×				D		×
[38]	×						×					M	×	
[48]		×					×		×			D		×
[33]		×	×				×				×	D		×
[50]						×	×	×	×	×		D		×
[42]			×	×	×	×			×			D	×	
[69]			×				×					S		×
[70]	×						×	×				D	×	
[35]		×					×		×			H, D, W	×	
[71]				×	×					×		D	×	
[72]						×				×		M	×	
[43]		×[C]	×[C]				×					D		×
∑	8	10	16	6	7	11	27	9	10	9	5	S:3, M:5, H:3, D:26, W:1	14	21

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