How Distributed Ledger Technology (DLT) Can Support Explainability in AI-based Algorithmic Trading

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Abstract

Algorithmic Trading is very often based on complex artificial intelligence models, which not uncommonly follow the black box principle, where system participants cannot understand the decision made by machine models.

The multitude of Machine Learning algorithms allows the realisation of different trading strategies, whereby more complex models such as neural networks can often make better predictions, but their decisions are all the less transparent and explainable.

Different tools, such as intrinsic and post-hoc interpretability, as well as model-specific or model-agnostic approaches, can be used to solve this challenge.

This analysis takes a new approach and shows how distributed ledger technology (DLT) can be used to support transparency and explainability in existing models or to develop entirely new approaches to creating transparency.

Furthermore, it provides conclusions, recommendations and suggestions for future research with the aim of advancing the field of explainable machine learning.

Keywords – algorithmic trading, artificial Intelligence, explainable artificial intelligence, machine learning, distributed ledger technology.

A. INTRODUCTION

1. Artificial Intelligence, Algorithmic Trading and Distributed Ledger Technology

The increasing spread of AI is due, on the one hand, to ever greater computing power, and on the other, to the massive spread of Big Data. Distributed Ledger Technology (DLT) and artificial intelligence (AI) have developed into a leading technology that enables innovation in nearly all industries. In this technical symbiosis, AI ensures that machines perform intelligent tasks that are usually performed by humans, while blockchain technology records and stores data and events chronologically in a transparent and unchangeable ledger system.

The financial industry is certainly one of the leaders in the use and development of AI (Zetzsche et al., 2020). Especially in Trading, AI algorithms are increasingly taking over decisions in all phases of the trading process.

The new complexity makes it difficult or even impossible for humans to keep track of the markets and make trading decisions in real time, while complex AI techniques such as neural networks can be implemented in near real time (Leshik and Cralle, 2011). At the same time the understanding and interpretability of trained artificial neural networks (ANNs) is a fundamental concern among AI practitioners and researchers (Bartram et al., 2020).

ANNs can be used for predictive modelling where they can be trained via a dataset. They use a variety of models (Linartados et al., 2020), defined at different level of abstraction and modelling different aspects of neural systems. ANNs require a large diversity of training samples for real operations.

ANNs are widely used for nonlinear function approximation (Dunis et al., 2016). They typically learn by a stochastic gradient descent, a type of hill climbing algorithm which represents a way of fitting a model to data (Sutton and Barto, 2018). In this context, it is elementary to estimate how a change in the individual connection weights would affect the overall performance of the network (Ertel, 2017).

Deep Learning (DL) as a special form of Machine Learning (ML) can achieve powerful processing. At the same time, in such a large-scale neural network, an extremely complicated relationship between input and output emerges with few possibilities to explain why a certain result was achieved.

The depth of the model is determined by the number of layers in the model. Deep neural networks are ANNs with many hidden layers. This often makes the overall approach more accurate and with less need for human guidance (Goodfellow et al., 2016). Deep neural networks generally outperform shallow neural networks (Abe and Nakayama, 2018).

2. Machine Learning Algorithms, Transparency, and Explainability

Recent DL models based on neural networks provide superior predictive power, but at the price of behaving as a black-box (Samek et al., 2019). They do not offer control or reasoning over its internal processes or outputs as opposed to glass-box models (Holzinger, 2018).

The lack of ability to explain internal data and the decisions made to a human is one of the main challenges of the new technology (Du et al., 2019; Escalante et al., 2018; Nassar et al., 2019). This might be even more important the closer the system operates to its boundary conditions.

3. Analysis

The central point of this analysis is the question of how the explainability of AI-based models of algorithmic trading can be supported by DLT technology and whether significant progress can be made in this field through the DLT-based support.

This analysis is organised as follows: After the introduction in the section A, which highlights the importance of Artificial Intelligence for Algorithmic Trading and emphasizes the requirements for explainable Artificial Intelligence and indicates a solution based on Distributed Ledger Technology, the following sections consider in more detail the state of the current literature and spot the key characteristics of underlying algorithms, methods, and technologies and their developments.

Section B briefly explains the connection between AI and algorithmic trading while Section C describes why we need explainable AI, which methods, techniques and taxonomies can be applied, and what their main characteristics and approaches are.

Section D shows the basic characteristics of Distributed Leger Technology and the functionality of smart contracts. Section E points to the synergies of the explainable Artificial Intelligence and Distributed Ledger Technology and presents the envisaged solution as an example.

The Analysis ends in Section F with conclusions, recommendations and suggestions for future research.

B. ARTIFICIAL INTELLIGENCE AND ALGORITHMIC TRADING

1. Algorithmic Trading and ML Algorithms

Algorithms play a significant role in all stages of a trading process (Nuti et al., 2011). This can be split into four stylized steps: pretrade analysis, trading signal generation, trade execution, and post-trade analysis (Figure 1).

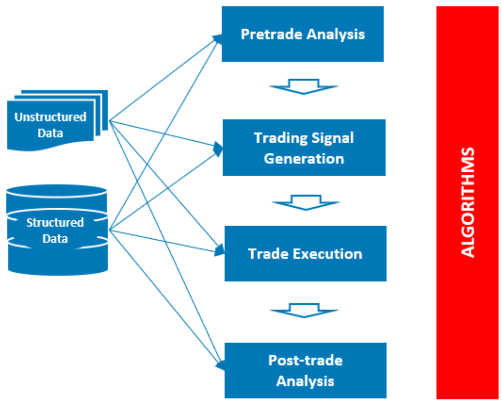

Figure 1: Steps at which the Algorithmic Trading System Components Occur (Own Representation with Partial Lean to Nuti et al., 2011)

Algorithmic Trading can be based on various ML strategies, all of which aim to check and use current market conditions to execute a buy or sell order with the intention of making a profit. None of these strategies can be equated with success. Rather, the question is when, where and how to use the right strategy.

The differences in AI algorithms and techniques are based on the type of data they work best with, the type of predictions they can make, the way they learn to adapt to the data, the computational power required for training, testing and deployment, and the ease with which they can be scaled up. The business strategy usually determines the structure of the data and the type of predictions to be obtained and thus also the choice of AI algorithm.

2. Related Work

Bartram et al. (2020) identify several AI techniques widely used for algorithmic Trading while Jansen (2018) takes a holistic perspective on the application of ML in the field of investment and trade.

Ellaji et al. (2021) compare the profitability in trading and investment in the financial market of conventional versus AI methods. They consider advantages and disadvantages of AI trading, success and risk, and budget and maintenance aspects.

Aziz and Dowling (2019) provide an application overview of ML and AI techniques and their benefits in risk management.

C. EXPLAINABLE ARTIFICIAL INTELLIGENCE

1. Why Do We Need Explainable AI?

a. Introduction

Legal regulations, economic framework conditions, and the safeguarding of entrepreneurial know-how require explainable AI models that provide details and reasons for the decisions made. In particular in highly regulated financial markets, the black box AI is often not suitable to fulfil the legal requirements. There is no doubt that regulators are looking for appropriate mechanisms to curb breaches of ethics and fair play.

In order to overcome this problem, explainable or trustworthy AI (exAI) models are required. All the more, there is a need to understand when and how decisions are made by such systems.

In the context of AI and more specifically ML exAI can be seen as a characteristic of a model, denoting any action or procedure to clarify or detail internal functions.

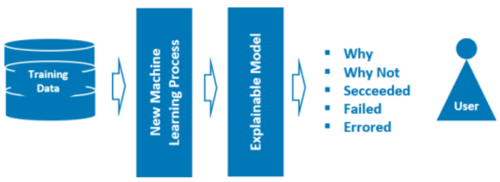

Figure 2: Framework for trustworthy artificial intelligence (Own Representation with Partial Lean to Turek, 2021)

It forms the interface between the human and the algorithmic decision-maker explaining its functioning clear and easy to understand (Figure 2). Their goals range from trustworthiness, causality, transferability, informativeness, confidence, fairness, accessibility, interactivity to privacy awareness (Preece et al., 2018).

Although transparency and explainability are important desiderata in algorithmic Trading, this transparency is often hidden and reserved only for the operators, if at all. This development has also triggered a number of controversies, because large players can use resources and algorithms that are used to the detriment of other especially for smaller market participants.

b. Related Work

The effectiveness of artificial intelligence (AI) systems is limited by the inability to explain the decisions and operations made (Shin, 2021).

Fairness, accountability, transparency and explainability (FATE) are inextricably linked to algorithmic complexity (Shin et al., 2020).

The interpretation of explanatory systems, including decision outcomes, must be immutable, tamper-proof and traceable with high reliability (Nassar et al., 2019).

Zhang et al. (2021) group the arguments for interpretability according to their importance into: High Reliability Requirements, Ethical and Legal Requirements and Scientific Use.

Atkinson et al. (2020) provide a comprehensive overview of the variety of explanatory techniques that have been developed in the field of AI and law.

2. The Interpretability

a. The Aim and the Definition

The terms interpretable and explainable are used interchangeably since a clear mathematical definition does not exist. Interpretability means the ability to present explanations in understandable terms to a human (Zhang et al., 2021; Arrieta et al., 2020; Molnar, 2021).

It can be defined as the degree to which a human can understand the cause of a decision (Miller, 2018) or can consistently predict the model's result (Kim et al., 2016).

The interpretability of an algorithm depends on its complexity. As AI systems and algorithms become more complex, they are also increasingly seen as 'black boxes' because more expertise and specialist knowledge are required to understand the AI decision or performance.

Linear and logistic regression models, decision trees and K-nearest neighbour classifiers, for example, represent easily understandable models (Bartram et al., 2020). Predictive decisions of neural networks, on the other hand, are considerably more difficult to comprehend and more or less represent an unsolved problem.

b. Related Work

Explainability gives certainty and confidence that AI systems work well, helps to understand why a system works in a certain way, and protects against prejudice (Shin, 2021).

The interpretability of a system is simply higher the easier the decisions and predictions can be understood (Molnar, 2021).

Zhang et al. (2021) provided a comprehensive review of neural network interpretability. They differentiate four commonly seen types of explanations: logic rules, hidden semantics, attribution and explanations by examples.

Zetzsche et al. (2020) address the regulatory challenges of AI in finance and emphasise the need for human involvement.

Carvalho et al. (2019) present an assessment of the current state of the machine learning interpretability research field, with an emphasis on societal impact and developed methods and metrics.

3. Methods, Techniques, and Taxonomies

a. The Challenge

Explaining the functioning of complex algorithmic decision systems and their rationality is a technically challenging problem.

Once we know that we need an interpretable machine learning approach the question is to determine how to evaluate it and if a taxonomy of evaluation that might be considered appropriate exists. Users, laws and regulations, explanations and algorithms represent the characteristics against which these explanation methods can be evaluated in terms of their appropriateness.

The methods for machine learning interpretability can be classified according to various criteria like intrinsic and post-hoc interpretability, model-specific and model-agnostic tools, local and global interpretations methods, visual interpretation and many more. However, alternative systematisations are also proposed (Zhang et al., 2021).

b. Related Work

Zhang et al. (2021) propose a taxonomy organized along the type of engagement (passive vs. active), the type of explanation (examples, attribution, hidden semantics, rules), and the focus (local vs. global).

Rosenfeld and Richardson (2019) provide the taxonomy of explainability in terms of interpretability, transparency, explicitness and faithfulness.

4. Intrinsic Interpretability and Post-hoc Interpretability

a. Interpretable Machine Learning

Interpretable machine learning techniques can basically be divided into two categories: Intrinsic interpretability and post hoc interpretability, depending on the time at which interpretability is achieved (Molnar, 2021).

In intrinsic methods, interpretability is realised by constraining the complexity of the machine learning. It is achieved by constructing self-explanatory models that incorporate interpretability directly into their structure. Decision trees, rule-based models, and linear models, for example, belong to this category.

The post-hoc or model-agnostic methods, on the other hand, analyse interpretability by training the models. Thus, the post-hoc variant requires the creation of a second model to provide explanations for an existing model.

The biggest difference between the two groups of models is the trade-off between model accuracy and explanatory fidelity. While intrinsic methods provide accurate and undistorted explanation, they sacrifice predictive performance. The post-hoc models are limited in their approximation, while the underlying model accuracy is preserved (Du et al., 2019).

b. Related Work

Molnar (2021) present the historical development of interpretable machine learning (IML), give an overview of modern interpretation methods and discuss the challenges.

Murdoch et al. (2019) wonder how the multitude of proposed interpretability methods relate to each other and what common concepts can be used to evaluate them. They introduce a categorisation of existing techniques into model-based and post-hoc categories, with sub-categories such as sparsity, modularity and simulatability.

Sileno et al. (2018) promote the use of normware for dealing with requirements of trustworthiness and explainability.

Carvalho et al. (2019) see the main reason that the interpretability problem remains unsolved is that interpretability is a very subjective concept and therefore difficult to formalise. They consider interpretability to be a domain-specific term and conclude that there can be no universally accepted definition. Consequently, they argue that ML interpretability requires considering the application domain and use case for each specific problem.

5. Local and Global Interpretation Methods

a. Differences and Similarities

Local interpretation methods explain a single prediction while global interpretation methods explain the entire model behaviour. For the latter, one needs knowledge about the algorithm and the data. This involves understanding how the model makes decisions based on a holistic view of its features and each of the components learned, such as weights, other parameters and structures.

Although there is no real consensus on what interpretability is and how to measure it if necessary, there are attempts to evaluate the approaches. These are designed at the application level (real task), human level (simple task) and functional level (proxy task) (Doshi-Velez and Kim, 2017). Even if it is not clear how to measure these properties, if we take a closer look at the properties of explanation methods we can judge how good they are (Robnik-Sikonja and Bohanec, 2018).

b. Related Work

Robnik-Sikonja and Kononenko (2008) present an approach to explanation of predictions, which generates explanations of predictions for individual instances and can be used with any classification method that outputs class probabilities.

Robnik-Sikonja and Bohanec (2018) present an overview of perturbation-based approaches which primarily support the explanation of the individual predictions, but can also visualise the model as a whole.

6. Model-specific and Model-agnostic Tools

a. Model Limitations

Model-specific interpretation tools are limited to certain model classes, while interpretability is achieved by restricting the complexity of the machine learning model.

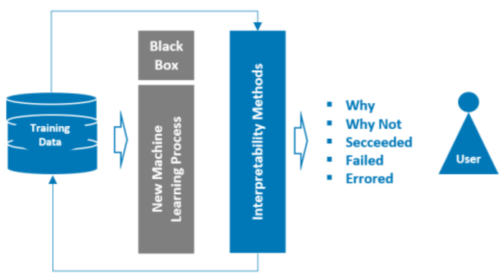

Figure 3: Schematic Diagram of the Explainable Machine Learning Model-agnostic Approach (Own Representation)

Model-agnostic tools, on the other hand, can be applied to any machine learning model after the model has been trained (post hoc).

Model-agnostic methods treat the machine learning models as black-box functions (Figure 3). They are model-independent and are applied post hoc (after the model has been trained). Per definition, they do not have access to model internals, e.g. weights or structural information.

b. Related Work

Ribeiro et al. (2016a) argue that this provide crucial flexibility in the choice of models and outline the main challenges for such methods. They further propose LIME, an explanation technique that explains the predictions of any classifier by learning an interpretable model locally around the prediction (Ribeiro et al., 2016b).

Example-based explanations are common forms of model-agnostic methods. Selecting particular instances of the dataset they try to explain the behaviour of the learning model or of the underlying data distribution (Molnar, 2021). Prominent representatives of these methods are counterfactual explanations, adversarial examples, prototypes, influential instances and k-nearest neighbors model.

Wachter et al. (2018) propose counterfactual explanations, which describe the smallest change to the world that can be made to obtain a desirable outcome or to arrive at the closest possible world without having to explain the internal logic of the system.

7. Artificial Neural Networks (ANNs)

a. Ho to Explain ANN?

To make predictions with a neural network, the data input is passed through many layers of multiplication by the learned weights and non-linear transformations. A single prediction can involve an infinite number of mathematical operations. Due to this complexity, interpretability is severely limited or often impossible for a human. Since neural networks hide features and concepts in their hidden layers, special tools are needed to uncover them.

b. Related Work

Vui et al. (2013) investigate different techniques for stock market forecasting using artificial neural networks (ANN) with the aim of providing an overview of the applications of ANN in stock market forecasting.

Kuo et al., (2001) indicate that neural networks considering both the quantitative and qualitative factors excel the neural networks reflecting only the quantitative factors both in the clarity of buying-selling points and buying-selling performance.

Shi and Zhao (2020) study the trend of price change in the stock market, using deep neural networks as classifiers for true and fake golden crosses to assess the growth trend of price change.

D. DISTRIBUTED LEDGER TECHNOLOGY

1. Basic Structure and Smart Contracts

One of the fundamental applications of blockchain technology is the management of transactions. In principle, blockchain refers to an immutable digital ledger, that relies on cryptographic techniques to capture and secure the data (Xing and Marwala, 2018; Casey et al., 2018).

The Framework of a Blockchain can be divided into three layers, Application Layer, Data Layer and Network Layer (Figure 4) .

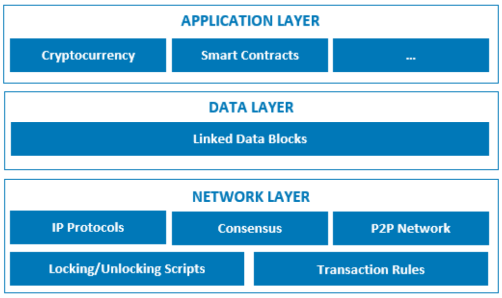

Figure 4: The Framework of a Blockchain (Own Representation with Partial Lean to Abbas and Sung-Bong, 2019)

The network layer enables connection to other users and achievement of consensus. The data layer contains the basic elements of the blockchain such as digital signature, Merkle tree and hash pointer.

Security in a blockchain network is achieved with the help of cryptographic hash functions, e.g. SHA-256, Keccak or RIPEMD-160.

Data in a blockchain is grouped together and organised into an ordered series of cryptographically linked blocks. The chain structure ensures consistency and prevents manipulation(Figure 5).

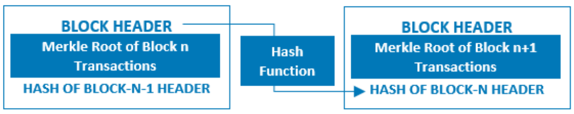

Figure 5: The Basic Structure of a Blockchain (Own Representation with Partial Lean to Sgantzos and Grigg, 2019)

Blockchain ensures high data integrity and forms a fertile environment for the creation of high-quality data through immutability (Sgantzos and Grigg, 2019).

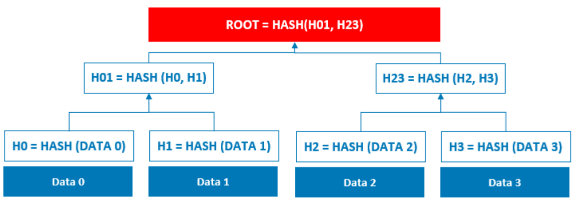

Figure 6: Merkel tree (Own Representation with Partial Lean to Yaga et al., 2018)

The application layer represents different applications, and the use of functions such as smart contracts, cryptocurrency, trading, etc.

Financial transactions are a good example to show how blockchain can add value to relatively complex systems (Bamberger, 2017). They are usually based on smart contracts and enable the automated execution of transactions based on previously defined rules.

Smart contracts are self-executing, autonomous protocols that facilitate, execute and enforce agreements between two or more parties (Szabo, 1994; Cant et al., 2016; Jani, 2020). What makes these legal agreements innovative is that their execution is made automatic through the use of algorithms. In fact, it is a collection of code and data that is deployed using cryptographically signed transactions on the blockchain network (Yaga et al., 2018).

Agreements in smart contracts are encoded in such a way that the correct irreversible execution is guaranteed.

2. Related Work

Vacca et al. (2021) review papers relating to smart contract testing, code analysis, metrics, security, Dapp performance, and blockchain applications.

Hu et al. (2021) provide a comprehensive overview of various schemes and tools that facilitate the construction and execution of secure smart contracts.

Hewa et al. (2021) examine significant smart contract applications and shed light on the future potential of blockchain-based smart contracts.

E. EXPLAINABLE ARTIFICIAL INTELLIGENCE AND DISTRIBUTED LEDGER TECHNOLOGY

1. AI and DLT Approach

a. How Blockchain Technology Can Help?

Distributed Ledger Technology provides a promising solution to solve the black box AI problem, in which predictions and decisions are recorded, stored, aggregated and managed using DLT (Nassar et al., 2019). It ensures important functions such as transparency and visibility, immutability, traceability and non-repudiation.

Since DLT can log every step in the data processing and decision-making chain, it opens the possibility of recording decisions and predictions in detail and allows it to be reviewed at any point in time. This gives users the ability to trace the decision-making process and understand the justification for decisions made.

The balance between performance and predictive accuracy and the explicability of the system can thus be more easily achieved. In less successful cases, DLT-based methods can help to trace who is to blame (Dinh and Thai, 2018).

b. Related Work

Salah et al. (2018) present a detailed survey on blockchain applications for AI and discuss open research challenges of utilizing blockchain technology for AI.

Pandl et al. (2020) review and synthesise existing research on the integration of AI with DLT and vice versa. They identify future research opportunities in the area of explainable AI, among others.

AI and DLT have distinct degrees of technological complexity and multi-dimensional business implications (Xing and Marwala, 2018). DLT enables AI agents to collaboratively perform consensus and save new decisions on the blocks which could be traced back and difficult to alter. Blockchain provides transparency and visibility of AI decisions to all participating AI agents on the network hence it becomes difficult for AI agents to alter or refuse the decisions. In addition, the programmable blockchain platforms enable SCs-based programming models for decentralized AI applications which ensure self-execution of AI agents based on predefined terms and conditions (Xing & Marwala, 2018).

Recording the decision-making processes on blockchains could be a solution to achieve transparency in order to gain trust.

Glaesser (2019) generally examines the question of whether transparent blockchain technology offers solutions to the problem of algorithmic fairness associated with opaque algorithms. He argues that blockchain can implement a "fairness by design" approach and integrate the "explainable AI" (exAI) approach to provide an understandable summary ex-post of why a certain decision was made by an algorithm.

Nassar et al. (2019) specify a framework for complex AI systems in which the decision outcomes are reached based on decentralized consensuses of multiple AI and exAI predictors (Figure 7).

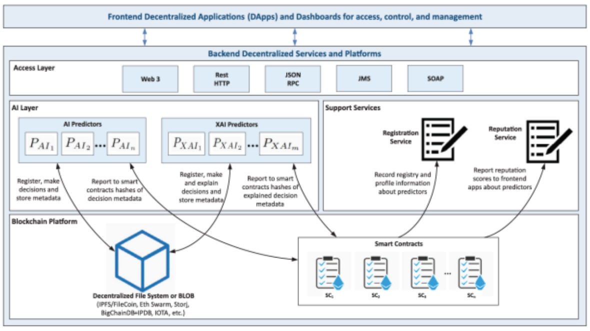

Figure 7: Proposed Blockchain Framework for Trustworthy Artificial Intelligence by Nassar et al. (2019)

The framework uses smart contracts to record and control interactions and create consensus for AI predictions and outcomes. They further claim that emerging distributed ledger technology seems the most adequate, if not the only one, to fulfil these requirements.

Malhotra et al. (2021) propose a blockchain-based framework that authenticates the evidence for exAI decisions. These are stored in the Inter-Planetary File System (IPFS) to circumvent storage restrictions on a blockchain. The hash of the declaration, on the other hand, whose storage requirement is low, is stored in the blockchain.

2. Proposed Algorithmic Trading Explainable DLT-Based Approach

The following basic model (Figure 8) shows the possible use of blockchain technology in the trading process.

Regardless of the algorithm used, all stages of the trading process can be recorded unchangeably. The results can then be evaluated immediately or at any later time.

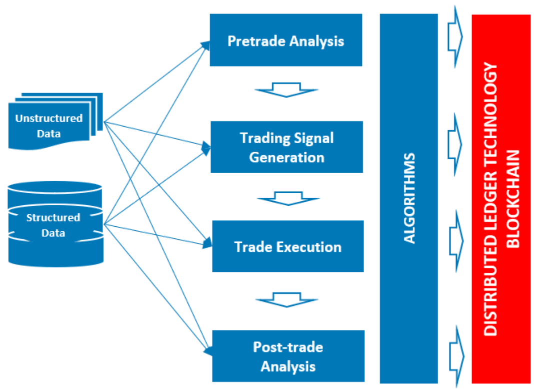

Figure 8: Basic Framework Structure for Explainable Algorithmic Trading Model (Own Representation)

Logging into the blockchain would take place on the basis of self-executing smart contracts. The choice of protocol, the type and extent of archiving of data, intermediate results and final results and the archiving frequency would depend on the business model and cannot be generalised.

F. CONCLUSION AND GUIDELINES FOR FUTURE WORK

There are many AI methods that can be used for algorithmic trading. The business logic and the structure of the data largely determine the choice of algorithms to be considered whereby the ability to make predictions generally increases with increasing complexity of the algorithm. At the same time, the required volume of data, the number of internal processing steps and the computer power increase disproportionately.

The increasing legal requirements for transparency call for solutions, even if these cannot be brought about or not without considerable effort. This transparency can be realised in different ways. The solutions range from local and global interpretation methods to model-specific and model-agnostic tools.

However, the combination of these models with DLT seems to be the most promising, as every step in the entire process from pre-processing to analysis can be recorded in immutable form and retraced at any time, immediately or even later.

The widespread prosperity of DLT should not obscure the fact that the technology is still in its infancy. Opening the black box of algorithmic decision-making still faces major technical obstacles. This analysis shows in principle that the trustworthiness of a model in terms of predictability, reproducibility, traceability and transparency can be significantly increased with the help of blockchain technology. However, it remains to be seen whether this technology can also be used for more complex models such as Artificial Neural Networks, whose speed basically exceeds the protocol capability of a Blockchain several times over.

Clearly, to explore the full potential of blockchain and AI in the context of exAI, extensive further research is required.

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