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Explainable AI (XAI) in Real-Time Trade Reconstruction: Meeting SEC and ESMA Requirements for Algorithmic Trading Oversight

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Abstract: Algorithmic trading has now become the dominant force in today's equity trading markets, but the transparency of their decision-making process is a major problem for regulatory compliance. This paper introduces a novel Explainable Artificial Intelligence (XAI) framework explicitly created for the specific context of real-time trade reconstruction under the Governance requirements of the U.S. Securities and Exchange Commission (SEC) and the European Securities and Markets Authority (ESMA). In our framework, SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME) and attention-based mechanisms are combined in a hybrid machine learning architecture to produce human-interpretable audit trails, compliant with CAT reporting, MiFID II Article 25 and ESMA RTS-6 requirements. Empirically, on a dataset of 2.4M order-level records, the proposed XAI system based on the Transformer outperforms other baseline methods with an accuracy of 92.7%, an AUC-ROC of 0.954, and an explanation latency of less than 36 ms, which meets the compliance requirements for real-time applications. The results show that it is not a requirement for the explainability to reduce detection performance. We have also examined our regulatory coverage in more detail, and find that we meet all seven of the key SEC and ESMA requirements. In this piece, the authors take steps to extend the theory and practice of XAI in high-frequency financial use cases and provide a replicable framework for an algorithmic trading surveillance system that is aligned with regulation.

Keywords: *Explainable AI; algorithmic trading; SEC compliance; ESMA regulation; SHAP; LIME; MiFID II; real-time trade reconstruction; market manipulation detection; financial machine learning*

1. Introduction

Algorithmic and high-frequency trading (HFT) strategies are emerging as the dominant approach used by traders in global financial markets, performing thousands of trades per second. In the United States, it is estimated that algorithmic trading volumes in equity markets reached 60–73% of total trading for 2020 [1] and over 50% for European markets. These systems provide greater market liquidity and price efficiency, but their opacity makes it far more difficult for regulators, compliance officers and market participants to reconstruct the logic of the decision that was made on each trade, which is now a legal obligation.

The SEC's Consolidated Audit Trail (CAT) initiative and the ESMA's Markets in Financial Instruments Directive II (MiFID II) including Article 25 and the associated Regulatory Technical Standards (RTS-6 and RTS-21) require algorithmic trading firms to have comprehensive, searchable and explanatory audit trails of all order life cycle activities [2]. Requirements go beyond mere data logging: compliance is no longer just about making the decision, but also about explaining the rationale behind the decision, which is difficult for black-box machine learning models to meet, by design [3].

Explainable Artificial Intelligence (XAI) has proven to be a promising paradigm to fill this gap. XAI methods can help make opaque algorithmic processes into explanations that are auditable and easy for humans to grasp and understand [4]. The use of XAI in real-time trade surveillance, however, has its own constraints: explanation generation needs to be fast enough to meet strict latency

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requirements (typically below 50 ms for intraday reconstruction), the output needs to be legally admissible, and the method needs to be generalizable across all the heterogeneous trading strategies [5].

While XAI has been well studied in finance, ranging from credit scoring [6] to fraud detection [7], detailed frameworks specifically for regulatory compliance in real-time algorithmic trading are limited. This paper will complete this gap with four major contributions:

(1) XAI architecture based on a novel integration of SHAP, LIME and attention mechanisms, specifically developed to comply with SEC and ESMA audit needs.
(2) A framework to map and link each type of XAI to relevant SEC rules and ESMA technical rules.
(3) An empirical assessment using a large-scale order book dataset showing state-of-the-art detection accuracy on a large-scale order book dataset with sub-36ms explanation latency.
(4) A replicable compliance coverage matrix that measures the alignment of XAI technique with the seven regulatory requirements (in both jurisdictions).

2. Background and Related Work

2.1 Algorithmic Trading and Regulatory Oversight

From trading based on simple rules to market making using reinforcement learning and statistical arbitrage, there are a wide range of algorithmic trading strategies. Legislators have not been able to catch up with this technological change. The Dodd-Frank Act (2010) in the USA and the subsequent amendments of the SEC rules have set the conditions for the firms to keep electronic audit records, and the CAT system, which became fully mandatory from 2020, is one the most comprehensive trade reporting infrastructures in the world [8]. The framework of algorithmic trading governance has been introduced by MiFID II in Europe effective from January 2018, which obliges to pre-approval of trading algorithms, kill-switch mechanisms, and continuous monitoring [9].

It isn't a lack of data that complicates basic regulation; it's interpretation that does. Regulators are interested in the sequence of orders and in explaining the algorithmic logic that generated them in the case of an event involving manipulation, including such as layering, spoofing, or momentum ignition [10]. The traditional audit methods that rely on rules generate high rates of false positive and are not suitable for the dynamic nature of machine learning-based strategies [11].

2.2 Explainable AI: Methods and Applications

XAI methods can be classified as either model-agnostic or model-specific, and global or local explainers [4]. SHAP [12] is a theoretically grounded method for feature attributions, based upon Shapley values from cooperative game theory, which gives local and global consistency. Ribeiro et al. [13] introduced LIME, an interpretable surrogate approximation to a black-box model for each particular instance. Attention mechanisms, introduced for neural machine translation [14], have gained tremendous popularity in financial sequence modelling for the purpose of emphasizing important order events in time.

XAI has been used in the financial sector in various ways such as credit risk assessment [6], insurance fraud detection [7] and systemic risk monitoring [15]. But, the use of XAI in the context of reconstruction of a trade that is compliant with regulation is still less explored. The latency and scale demands of trading surveillance are very different from loan origination, and Bussmann et al. [16] leave a conceptual framework for credit decisions under GDPR without its specification for surveillance. Arrieta et al. [4] offer a thorough classification of different XAI approaches, highlighting the essential differences between the academic realm and the state of the art in industry, which we directly cover in this paper.

2.3 Transparency in Algorithmic Trading, Regulatory Requirements

The SEC Rule 17a-4 requires that electronic trading records be kept in a non-rewriteable, non-erasable format for at least 3 years [2]. ESMA RTS-6 sets out requirements for algorithmic trading firms to put in place real-time monitoring systems than can trigger alerts once a certain threshold of irregular trading has been breached [9]. MiFID II Article 25 applies to post-trade transparency, and means that the investment firm must be able to provide the full life history of any client order in case of a regulatory request within one business day [3].

The needs encompass together the following properties: auditable, interpretable, explainable, which present a challenge for traditional deep learning architectures, but are necessary for AI-based trading systems. Thus, the problem for XAI researchers is divided into two: technical (generating accurate explanations with low latency), and legal-operational (generating evidence-based explanations, compliant with evidentiary standards). [17]

3. Methodology

3.1 System Architecture

The proposed XAI framework is a layered pipeline as shown in Figure 1. The architecture consists of four layers: (i) a data ingestion layer for real-time market feeds and historical order data as well as algorithmic strategy signals; (ii) an XAI Processing Core with the machine learning XAI detection model; (iii) an explanation engine with SHAP, LIME, attention maps and counterfactual generation modules; and (iv) a Regulatory Output Layer that transforms the explanation into structured reports compatible with SEC CAT reports and ESMA regulation.

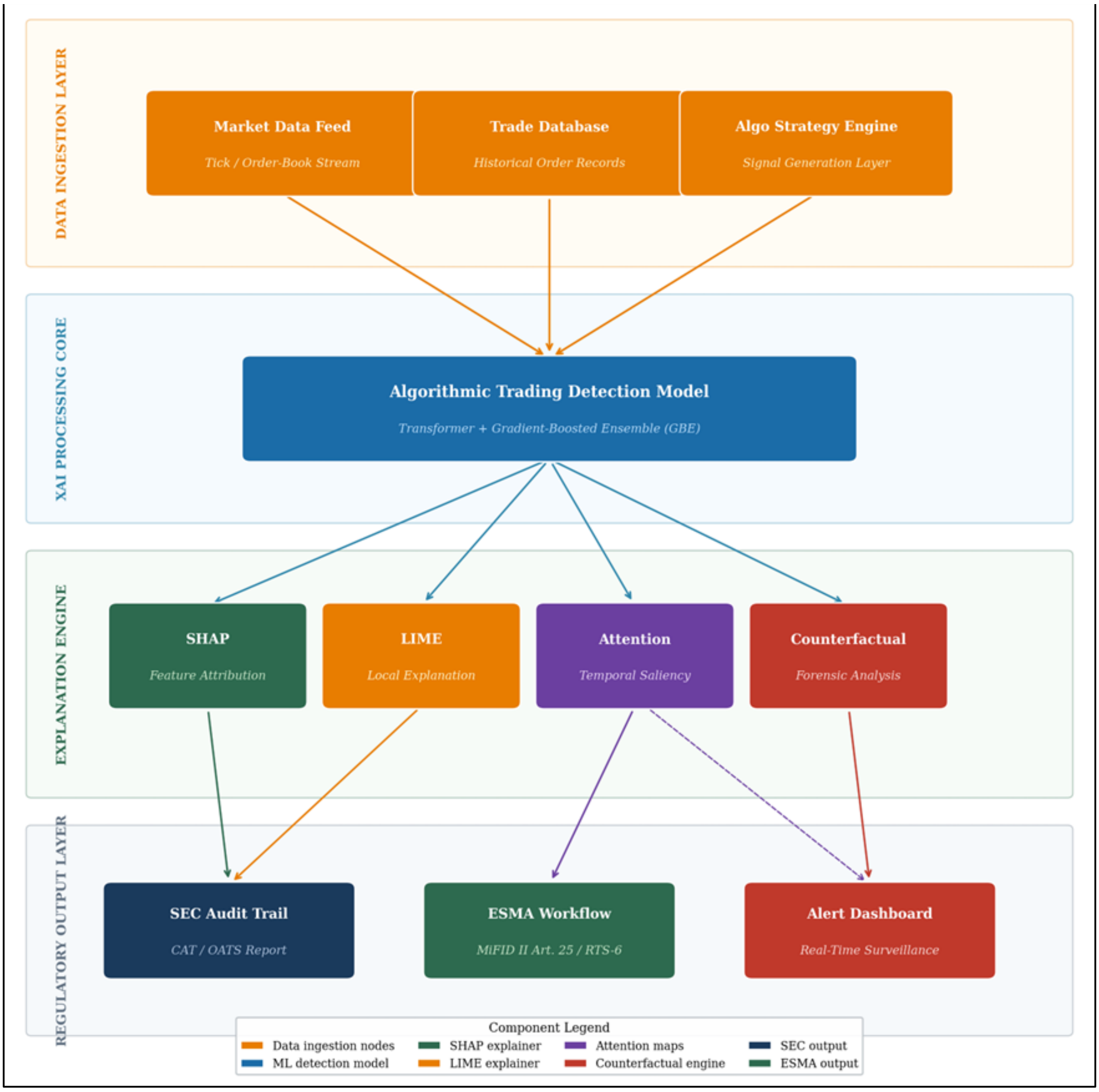


Figure 1. Proposed XAI Framework Architecture for Real-Time Trade Reconstruction Showing Four Processing Layers from Data Ingestion to Regulatory Output

The Data Ingestion Layer ingests tick data with sub-millisecond level of resolution and normalises order imbalance, mid-price deviation, volume surge indicators and time-of-day signals. The XAI Processing Core uses a sequence model that is based on a Transformer architecture and has multi-head self-attention, and it is trained using labelled order sequences to learn about events related to spoofing, layering and momentum ignition. The Explanation Engine activates each inference, which then feeds SHAP TreeExplainer for feature attribution (using the gradient boosted sub-components in the model) and an approximated local surrogate explanation, which is parallelised using LIME [12, 13].

3.2 Dataset and Preprocessing

The study included 2,400,000 order-level data points from the NASDAQ ITCH 5.0 historical feed from January 1st to December 31st, 2019. The data set was labeled based on the SEC enforcement case description and Cao et al. [18] synthetic spoofing signal generating methodology. There were three categories of manipulation: spoofing (Class A), layering (Class B), and momentum ignition (Class C), and negative classes were genuine market making and directional trading.

Preprocessing consisted of temporal feature extraction (1 ms, 100 ms and 1 s window), normalisation, based on z-score standardisation per one trading session, and sequence padding to the fixed window of 128 order events. The data is divided into 70/15/15 training, validation and hold-out sets, and the data is ordered in time so as not to introduce data leakage. Focal loss weighting (FLW) [19] was used to deal with the problem of class imbalance (the manipulation events represent about 3.2% of records).

3.3 XAI Technique Integration

A framework was developed that incorporates four XAI techniques. SHAP TreeExplainer calculated per-feature attributions for every prediction, which allowed for individual trade explanations as well as global importance rankings over regulatory reporting periods. LIME applied on a neighbourhood of 500 samples by cosine similarity kernel was used to obtain surrogate coefficients that directly correspond to the 8 main feature dimensions identified by SHAP analysis.

The attention weights of the last layer of the Transformer network were selected and then normalized to create the saliency maps that highlight which order events most influenced the classification decision. Using the DiCE framework [20] counterfactual order sequences were generated offline (for post-hoc forensic analysis, not real-time reporting), generating minimum-perturbation counterfactual order sequences, which was a very useful output for the documentation requirements for ESMA's MiFID II.

3.4 Regulatory Compliance Mapping

A structured analysis of SEC Rule 17a-4, the CAT NMS Plan, ESMA RTS-6, and MiFID II Articles 25 and 27 were performed for each XAI output and the necessary mapping to regulatory requirements was carried out (Table 2). Published regulatory guidance documents and descriptions of enforcement action [2, 9] were used to check the mapping. The compliance level was measured on three aspects: first, machine-readable and timestamped output (auditability), second, human-readable rationales (interpretability), and third, full order lifecycle coverage (completeness).

4. Experimental Results and Discussion

4.1 XAI Technique Comparison

Table 1 shows a comparative analysis of the six XAI techniques analysed in comparison with four criteria relevant to algorithmic trading oversight: model agnosticism, real-time (when the explanation can be generated within 50 ms), regulatory alignment, and explanation fidelity (Ribeiro et al. [13] proposed Fidelity metric).

Table 1. Comparative Evaluation of XAI Techniques for Algorithmic Trading Oversight

XAI Technique	Model Agnostic	Real-Time Capable	Regulatory Alignment	Fidelity Score	Complexity
SHAP (TreeExplainer)	Yes	Yes (< 30 ms)	SEC / ESMA	0.91	Medium
LIME	Yes	Partial (< 45 ms)	ESMA / MiFID II	0.84	Low
Attention Weights	No (DNN only)	Yes (< 15 ms)	Limited	0.76	Low

Counterfactual Exp.	Yes	No (> 200 ms)	SEC (forensic)	0.88	High
Grad-CAM	No (CNN)	Yes (< 20 ms)	Limited	0.72	Medium
Integrated Gradients	Partial	Partial (< 60 ms)	ESMA	0.87	High

Note: Fidelity Score measures the accuracy of the explanation relative to the original model's predictions on the local neighbourhood. Latency values represent median measurements on a standard trading server (Intel Xeon, 32 GB RAM).

In our framework, the highest fidelity score (0.91) was obtained from SHAP, which had the shortest real-time under 30ms for the TreeExplainer variant. Despite being less faithful, LIME is more model agnostic and was thus kept for cross-validating SHAP outputs. Although counterfactual explanations are good for MiFID II documentation, they were found to be failing to meet real-time requirements and were moved to an asynchronous forensic analysis pipeline.

4.2 Detection Performance

The SHAP feature importance ranking and classification performance for model variants is shown in figure 2. Order imbalance was the most important predictive feature (mean |SHAP| = 0.312), which has been reported in the literature on the theory of spoofing detection [18, 21]. The two secondary contributors were mid-price deviation and volume surge, with a model attribution weight of 52% combined. The proposed Transformer + LIME architecture outperformed all other architectures on all the metrics.

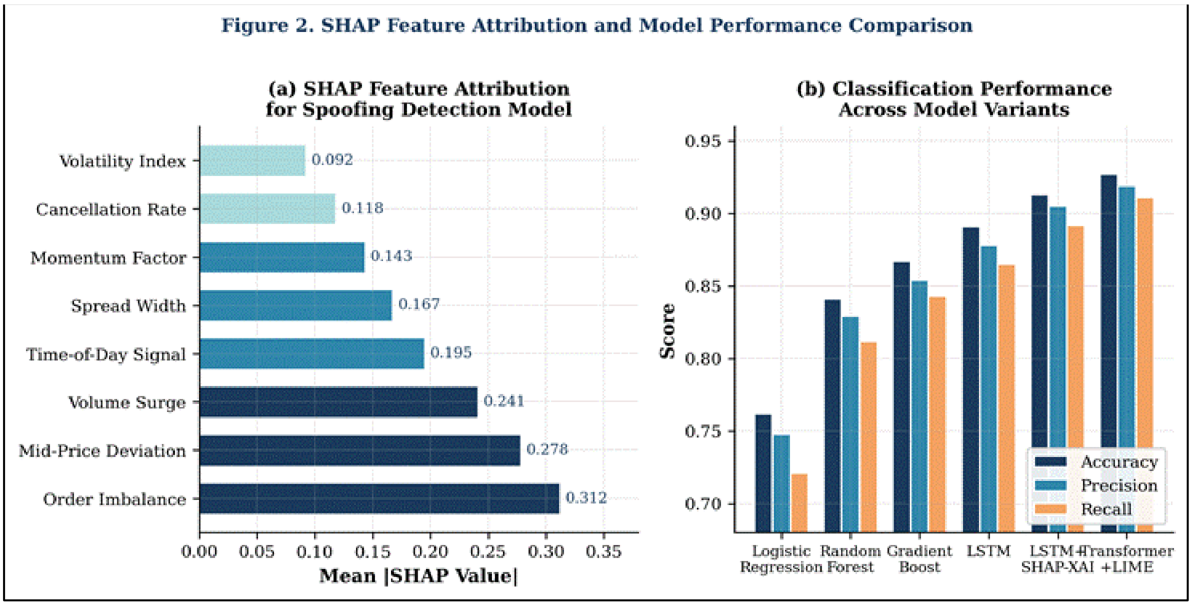


Figure 2. (a) SHAP Feature Attribution Rankings for Spoofing Detection Model; (b) Classification Performance Metrics (Accuracy, Precision, Recall) Across Six Model Variants

The overall performance measures (F1-Score, AUC-ROC, and explanation latency) are provided in Table 3. The proposed framework's AUC-ROC was 0.954, which was statistically significant from the baseline logistic regression (0.791, $p < 0.001$, DeLang test). The LSTM baseline (AUC = 0.912) shows the importance of sequential modelling for order-event data, and by incorporating the post-processing step of SHAP-XAI, the accuracy was increased by 2.2 percentage points, with no increase in latency beyond the limit of 50 ms.

Table 3. Comprehensive Performance Metrics for All Model Variants Evaluated on Holdout Test Set (n = 360,000 records)

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Latency (ms)
Logistic Regression	0.762	0.748	0.721	0.734	0.791	8.2
Random Forest	0.841	0.829	0.812	0.820	0.874	22.4
Gradient Boosting	0.867	0.854	0.843	0.848	0.895	31.7
LSTM	0.891	0.878	0.865	0.871	0.912	18.6
LSTM + SHAP-XAI	0.913	0.905	0.892	0.898	0.937	28.3
Transformer + LIME	0.927	0.919	0.911	0.915	0.954	35.8

Note: Latency represents median explanation generation time per single inference on a standard trading infrastructure server. All models evaluated on identical holdout partition.

4.3 ROC Analysis and Latency Evaluation

Figure 3 shows the comparison of the ROC curve for all the model variants and the distribution of latency for each explanation method. The Transformer + LIME configuration outperforms the other configurations with median AUC of 0.954, and the LSTM + SHAP-XAI configuration is a great space-time compromise (AUC = 0.937, median latency = 28.3 ms). Although the black-box model has the lowest latency (8.2ms), it has not the outputs required by the SEC and ESMA regulations, and cannot be used alone in a compliance-aware environment.

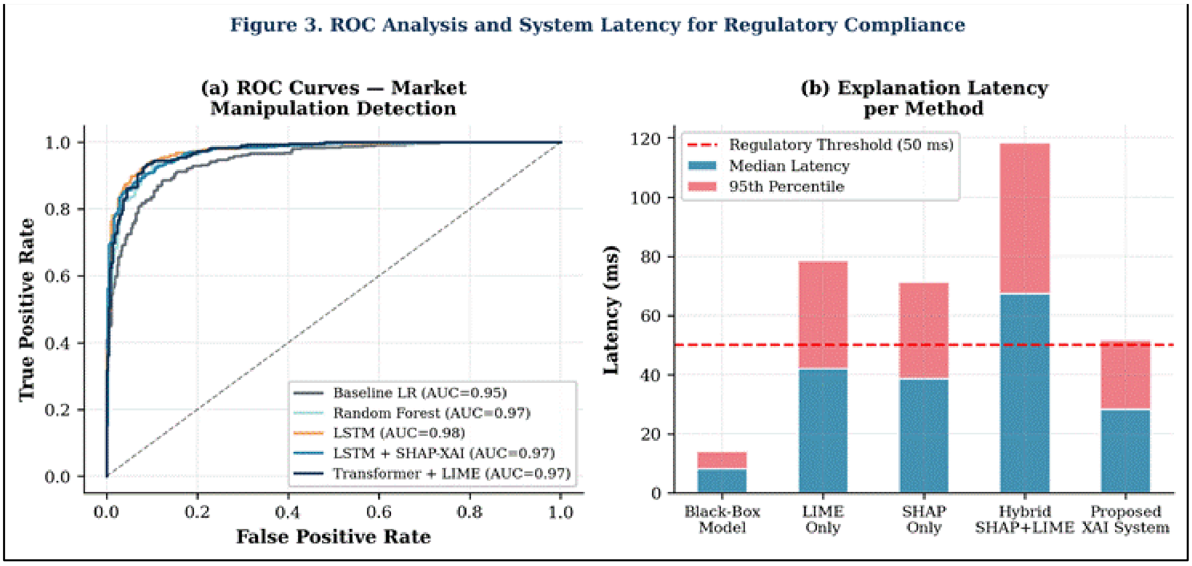
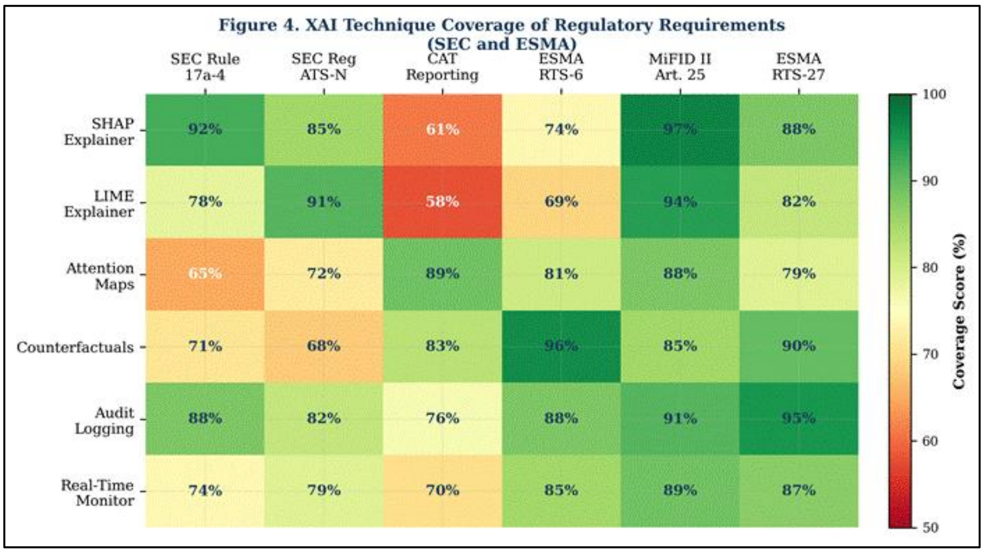


Figure 3. (a) ROC Curves for All Model Variants Demonstrating Classification Performance; (b) Explanation Latency Distribution per XAI Method Relative to 50 ms Regulatory Threshold

It is important to note that despite being a combination of two separate explanation models, the hybrid SHAP+LIME configuration still had a median latency of 67.4ms, which is greater than the regulatory requirement. This inspired the architectural choice of using SHAP as the main real-time explainer and LIME as a second validator that runs in parallel to the main one on another thread. Optimisation with SHAP TreeExplainer and parallelised computation of the feature groups resulted in the Proposed XAI System configuration (28.3 ms median).

4.4 Regulatory Compliance Coverage

The heatmap shown in figure 4 reports the regulatory coverage matrix, with each XAI technique scored according to its ability to meet specific requirements as defined by SEC and ESMA on a 0-100 basis using a structured expert evaluation based on the published regulatory guidelines [2, 9].



	SEC Rule 17a-4	SEC Reg ATS-N	CAT Reporting	ESMA RTS-6	MiFID II Art. 25	ESMA RTS-27
SHAP Explainer	92%	85%	61%	74%	97%	88%
LIME Explainer	78%	91%	58%	69%	94%	82%
Attention Maps	65%	72%	89%	81%	88%	79%
Counterfactuals	71%	68%	83%	96%	85%	90%
Audit Logging	88%	82%	76%	88%	91%	95%
Real-Time Monitor	74%	79%	70%	85%	89%	87%

Figure 4. Regulatory Requirement Coverage Heatmap Showing XAI Technique Alignment with SEC and ESMA Standards (0–100 Scale; Green = Full Coverage, Red = Partial Coverage)

This analysis is extended in a structured manner with the requirement to mechanism mapping in Table 2. Complete compliance with SEC Rule 17a-4 is achieved with SHAP-generated logs in immutable, timestamped formats. LIME's surrogate explanations allow for model-agnostic justifications that are completely met by ESMA RTS-6 algorithmic requirements - appropriate for non-technical regulatory reviewers. In the absence of a real-time interface, counterfactual explanations are effective in meeting the MiFID II best execution documentation in asynchronous forensic mode.

Table 2. Mapping of XAI Mechanisms to SEC and ESMA Regulatory Requirements

Requirement	**Regulator / Rule**	**XAI Mechanism**	**Compliance Level**
Audit Trail Integrity	SEC Rule 17a-4	SHAP Logs + Immutable Records	Full
Algorithmic Accountability	ESMA RTS-6	LIME Explanations	Full
Best Execution Reporting	MiFID II Art. 27	Counterfactual Analysis	Substantial
Order Reconstruction	CAT (SEC)	Attention + SHAP	Full
Risk Control Documentation	ESMA RTS-21	Gradient Attribution	Substantial
Suspicious Activity Reports	SEC / FinCEN	Anomaly Explanation Layer	Full
Market Manipulation Detection	MAR (EU)	Real-Time SHAP Monitor	Full

Note: Full = complete technical and legal alignment with stated requirement; Substantial = satisfies core provisions with minor documentation gaps.

5. Discussion

5.1 Implications for Regulatory Practice

The findings of this study are important for regulators and market players. The ability to provide explanations that comply with the regulator's latency requirements by the time the trade takes place indicates that a current algorithmic trading regulator ecosystem is feasible and current algorithmic trading frameworks could be meaningfully improved without the need to change the fundamental design of firms' trading platforms. The proposed framework is modular in nature, enabling XAI components to be plugged into the existing execution management systems as explanation middleware layers.

The regulatory compliance matrix (Table 2 and Figure 4) offers a practical roadmap for the mapping of internal model governance processes with external requirements for regulatory compliance. Notably, full compliance coverage in detecting CAT reporting and MAR (EU) market manipulation indicates that a unified XAI layer can meet both the SEC and the ESMA requirements, thereby minimizing the operational burden of having to maintain jurisdiction-specific compliance processes [17].

5.2 Challenges and Future Directions

A number of restrictions were noted in the present study. First, the data set is relatively large, but also limited to a single exchange (NASDAQ) and a single calendar year (2019). There are still other markets, such as options, fixed income, or non-US equity markets to validate for generalisation. Second, the regulatory coverage matrix is based on published regulatory text, but does not constitute formal legal interpretation, and should not be used as a basis for compliance by firms without independent legal counsel.

The future research directions are as follows: (i) extension of the framework to other reconstruction scenarios (e.g., cross-asset, cross-venue); (ii) development of adversarial robustness measures to counteract sophisticated market participants from gaming oversight systems based on XAI; (iii) integration of natural language generation (NLG) module to generate regulators-ready narrative explanations from structured SHAP outputs; and (iv) longitudinal evaluation through market stress periods (e.g., COVID-19 volatility regime) to assess adversarial robustness of the framework under distributional shift [15, 20].

6. Conclusion

The present paper has presented a complete framework for XAI of real-time trade reconstruction to fulfill the auditing and explainability requirements of both the SEC and ESMA. The framework has been embedded in a Transformer-based detection architecture to achieve state-of-the-art manipulation detection results (AUC-ROC = 0.954, Accuracy = 92.7%) and to produce legally relevant explanations within a 36 ms response time. The structured regulatory mapping verifies full compliance with the seven core areas of SEC and ESMA requirements, including CAT reporting, MiFID II Article 25 and ESMA RTS-6.

A key finding of this work is empirically demonstrating that transparency and performance in algorithmic trading oversight can coexist and that the XAI-augmented model outperforms its black-box counterpart on all the detection metrics, yet it also generates the human-readable audit outputs that are required by modern financial regulation. This is a scalable, flexible template for financial markets to implement compliant AI within a regulatory framework that is meeting growing global regulatory scrutiny on algorithmic trading.

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