Regulatory Overview and Implications from Critical review

The following critical review *"Can Machine-Learning Techniques Be Applied in High-Frequency Trading Despite Their Black-Box Nature?"*—evaluates Deep Q-Learning and other reinforcement-learning execution agents in global HFT venues. While the paper is academic in scope, its core findings map directly onto ASIC's surveillance remit:

- Transparency risk: Deep-RL order-routing bots can mask latency-style liquidity provision behind opaque reward functions—exactly the micro-volatility ASIC highlighted in REP 597 (2018).
- Model robustness: Adversarial order-book spoofing can mislead black-box agents; this parallels market-quality concerns raised in CP 202 and REP 452.

By converting these insights into a focused, 90-day prototype, ASIC's Market Integrity team can test whether modern ML surveillance augments existing SMARTS rule-sets and enhances compliance with the "fair, orderly, and transparent" mandate in **s 798H(1)(b) Corporations Act 2001**.

Regulatory Instrument	**Relevance to ML-HFT surveillance**
REP 597 & follow-up **REP 798 (2024)**	Confirm latency-driven liquidity provision remains a structural feature in AUD/USD futures and equity indices; recommend ongoing analytics on queue-position & order-modification rates.
RG 265 – Market Integrity Rules Obligations	Requires venues and participants to prevent or detect manipulation; ML anomaly scores can be embedded as an additional control.
Corporations Act s 798H(1)(b)	States markets must be fair, orderly, transparent; real-time ML flags support proactive rather than reactive enforcement.
ASIC Derivative Transaction Rules (Reporting) 2024 – Table S1.1	Although aimed at OTC derivatives, the ISO 20022 **auth.030** message already captures latency-relevant fields (e.g., ExecutionTimeStamp, TransactionPrice, PlatformIdentifier) that can feed an Isolation-Forest model.

90-Day Lab Prototype Proposal

Phase (Calendar Days)	Objective
0–15 d	Ingest one month of full-depth AUD/USD futures & spot AUD/USD order-level data into the Market Integrity data-lake.
16–45 d	Feature engineering + Isolation Forest model training.
46–60 d	Live “shadow-mode” scoring in KDB-on-Kafka stream.
61–75 d	Analysts review top-25 anomaly episodes; compare to existing SMARTS alerts.
76–90 d	Draft **Internal Enforcement Referral** template for when ML flag aligns with MIR breach indicators.

Deep-RL execution agents will reach Australian OTC-FX and futures desks. ASIC’s existing data feeds—augmented with the fields above—provide a foundation for Isolation-Forest anomaly scoring that can surface latency-linked misconduct ahead of visible price spikes.

Regulatory next step: form a small cross-functional squad (Surveillance + Data + Legal) to run the 90-day lab, after which Enforcement can adopt the referral workflow if precision targets are achieved.

Continuous ML surveillance, aligned with REP 597 insights and the transparency standard in s 798H, positions ASIC to stay ahead of increasingly automated liquidity strategies without sacrificing interpretability or due-process.

Critical Review

Can Machine Learning Techniques Be Applied in High Frequency Trading Despite Its Blackbox Nature?

Abstract

This paper critically examines the application of Machine Learning (ML) in High-Frequency Trading (HFT), addressing its efficacy amidst concerns about its 'black box' nature using recent, peer-reviewed literature. At the core, sophisticated mathematical models within ML capture complex, non-linear relationships and process large datasets efficiently, essential for predictive modelling in the fast-paced HFT environment. Despite these advantages, the opacity and complexity of ML models raise significant security and interpretability issues, which are critical given HFT's rapid and sometimes obscure nature. This review highlights recent advancements that enhance transparency and improve market stability and explores the development of algorithms for detecting adversarial attacks, thus addressing some of the critical vulnerabilities of ML in HFT. Furthermore, the review discusses specific ML strategies such as Deep Q-Learning and Genetic Algorithms, demonstrating their role in stabilising markets and enhancing the robustness of trading strategies. By delineating these technological advancements, the paper underscores the evolving utility of ML in HFT and advocates for continued research to optimize and safely implement these innovations in trading.

1. Introduction

The financial market environment has experienced significant growth in the last few decades for many reasons, one being the technological advancements in Machine Learning (ML) and its application in High-Frequency Trading (HFT). HFT involves immense data analysis and requires advanced predictive abilities due to its fast-paced model, prompting research into ML's suitability in HFT. Current research into ML's use in HFT stems from applying sophisticated mathematical formulas, enabling models to capture non-linear relationships and analyse data efficiently.

Demonstrating this capability, ML's Neural Networks (NN) allow for simultaneous linear and non-linear data analysis while omitting dependence on assumptions typically made by linear models, resulting in superior performance. In one study, NN outperformed linear models predicting monthly agricultural trading volumes (Xu & Zhang, 2023). ML Classifiers such as Random Forests and XG Boost Models also highlight ML's efficient data analysis capabilities. Features from technical indicators that could not be previously obtained are extracted, consequently improving strategies when used in conjunction with other algorithms (Lohrmann & Luukka, 2019). Support Vector Machines (SVM) are also a point of interest for their flexibility and effectiveness in creating hyperplanes that efficiently separate data points into classes, even in high-dimensional spaces. This capability is crucial for managing the complex datasets typically found in HFT (Akyildirim et al., 2022).

High Frequency Trading's speed reaches theoretical speeds of light (Zaharudin et al., 2022) and creates vast amounts of data to be processed by exchanges and firms hence critics claim that immense data requirements of HFT necessitate ML techniques to be utilised. This consequently improves the performance of systems based on experience and data without requiring explicit programming (Ferrouhi & Bouabdalaoui, 2024). Leveraging ML techniques has become a cornerstone of many HFT algorithms due to their execution and predictive prowess (Xu et al., 2023).

In contrast, it should be noted that ML brings issues regarding its complexity and security, critics claim. ML's complexity is typically described as a black box as it does not explain its predictions comprehensibly (Rudin, 2019), sparking contention in its applications further exacerbated by HFT's inherent speed and complex nature that already can cause market issues (Zaharudin et al., 2022). Although the capability to learn on its own was the driving force of its development, it begs the question of whether an algorithm can modify itself to be a detrimental algorithm unbeknownst to the developers, possibly causing market instability due to the algorithm's supposed self-improving nature (Lee & Schu, 2022).

Moreover, its susceptibility to adversarial attacks is also a factor to consider in its applications within HFT. These attacks are small changes to the model's inputs but significantly change the model's outputs (Schwarszschild et al., 2021), resulting in the need for top security and reliability of ML algorithms. These perturbations are also difficult to intervene in because of HFT's speed. Perturbations such as spoofing are easy to conduct but difficult to punish due to their ambiguity, as they involve sending orders to an order book with the intention to cancel to mimic market activities. ML algorithms that analyse the order book will account for the fake orders as genuine orders (Stenfors et al., 2023) and consequently make decisions based on false information. The aim of this review will be to evaluate the suitability of Machine Learning Techniques in HFT by critically analysing recent peer-reviewed literature.

2. Machine Learning Black Box Nature Induced Dilemmas

ML's advantages include its efficient data-driven approach to solving problems whilst maintaining relatively lightweight computations (Kercheval & Zhang, 2014). However, its advantages are not without its constraints. ML technique's prediction is accompanied by a level of uncertainty (Barandas et al., 2022) as it learns from input data, exposing itself to time series noise, consequently leading to unexpected model implications. This uncertainty goes hand in hand with ML's general difficulty of interpretability, evidence of ML's inherent black box nature (Rudin, 2019). This black box nature can be deemed risky when combined with HFT speed of execution since issues that arise within an ML algorithm would be difficult to stop without some HFT algorithms acting upon the issues. Risks include adversarial attacks and market instability in the form of spoofing and herding behaviour.

2.1 *Induced Market Instability*

ML models' black box nature poses significant challenges in high-frequency trading, notably promoting herding behaviour due to their inscrutable decision-making processes. This complexity necessitates transparency and interpretability in ML models to counteract adverse behaviours such as herding, underscored by Makridakis et al. (2017). Further empirical support is provided by Ballis and Anastasiou (2023), finding that following the deployment of advanced neural networks like ChatGPT revealed an increase in cross-sectional standard deviation (CSSD) among heavily traded assets. This rise suggests a direct link between adopting sophisticated ML tools and heightened herding behaviour. Furthermore, Gensler & Bailey (2020) propose Deep Learning, an ML subset, as an actor in undermining market stability by mapping its characteristics to five pathways in which it may lead to market instability and attributes herding as one issue. Albeit an informative study, it lacks scientific methodology to substantiate claims.

Nonetheless, the potential of ML technologies, especially reinforcement learning (RL), to exacerbate market risks is still recognised. The OECD (2012) reports that ML intensifies risky trading behaviours, a finding supported by Lussanage et al. (2024), who found a positive correlation between the learning rates of ML models and the occurrence of market crashes. These results, albeit derived from simulations, are rendered credible by their realistic settings, based on multi-agent systems (MAS) that faithfully mimic essential market behaviours like fat-tail log returns, power-law volatility autocorrelation decay, and volatility clustering, as per Lipski & Kutner (2018). This evidence advocates for further investigation of ML technologies in trading systems, with a strong emphasis on rigorous oversight and continuous validation to manage their impact on market stability effectively.

On the other hand, spoofing, where one places orders to create fabricated market supply or demand, academic literature suggests, undermines market stability (Azzutti et al., 2022).

Research by Martinez-Miranda et al. (2015) finds that ML models in HFT, particularly RL, can divert their trading activities towards spoofing activities to maximise an objective and inadvertently promote market instability. In addition to this, the HFT landscape, Aldridge (2013) finds, is already replete with spoofing. Significant R^2 relationships were found between the number of order cancellations vs the number of real executed orders in exchanges with higher liquidity, thus straining market stability. Khomyn and Putnins (2021) specify that high order rates strain exchanges due to operational data processing conducted by exchanges. Additional research could be done to see if other ML models would show similar results or if this is unique to RL models. A more comprehensive set of statistics across more variables associated with HFT would establish stronger evidence as Aldridge's (2023) study does not holistically reflect HFT circumstances.

2.2 Adversarial Attacks

ML models require input data to train on, making them susceptible to adversarial attacks and raising issues in their applicability in HFT. Goldblum et al. (2021) demonstrate this by making a range of realistic attacks and perturbations against three different neural network models, establishing that even rudimentary attacks can impact models. The research methodology is designed scientifically. However, it lacks synthesised evidence to fulfill the aim of the investigation. Albeit connections between the study variables are made, substantiated conclusions failed to be drawn to contribute to academic literature.

Natural Language Processing (NLP) is another subset of machine learning that is prone to adversarial attacks. HFT systems can leverage NLP to gauge market sentiment by analysing social media and news articles (Sarjine et al., 2024). Research by Xie et al., (2022) solved combinatorial optimization problems associated with social media platform X and successfully misled three different deep learning models, incurring losses in their simulated portfolio. Figure 1 denotes one of their findings, demonstrating how small changes can change a model's output. This study's methodology is robust and accounts for the overall ML trading landscape, including HFT. Its comprehensive methodology fulfills the paper's aim rigorously and notably finds that only changing one word can cause a 32% additional loss to their simulated investment portfolio, contributing to academic literature.

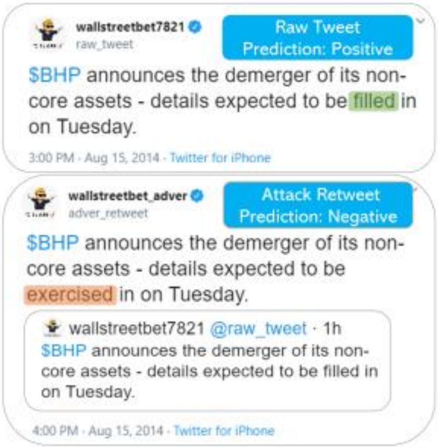

Figure 1: Two tweets demonstrating how one small change in a tweet can change the models output (Xie et al., 2022).

Nehemya et al. (2021) concur that machine learning models are vulnerable to adversarial attacks that target its inputs and tested this by manipulate a data stream by adversarial means. Evidence reinforced HFT systems are highly vulnerable to adversarial inputs as minor adversarial perturbations to a data stream could mislead multiple models due to shared vulnerabilities of models that utilise the same data stream. The study maintained a robust methodology, and they fulfilled their aim; however, the data that was used to carry out the experiment was from a widely used public source. Security is not their focus, and although strong evidence is presented, its applicability in the real world is questionable as data vendors typically have stronger security measures.

3. Robust Machine Learning Techniques Applied in High Frequency Trading

Sophisticated mathematical models underpin ML models and provide a foundation for effective predictive modelling in HFT. These models capture non-linear relationships in financial markets, enabling traders to predict market movements accurately (Lee et al,. 2021). By analysing vast datasets rapidly and efficiently, ML models offer significant advantages in a domain where speed and accuracy are paramount (Huang et al., 2019; Lahmiri & Bekiros, 2021). The mathematical sophistication implementation of these models has consequently led to improved predictions of market dynamics.

However, the complexity and opacity of ML models raise concerns regarding their security and interpretability. Recent advancements in ML have begun addressing these concerns by enhancing model transparency and developing algorithms specifically designed to bolster market stability and detect adversarial attacks. For instance, improved algorithms not only contribute to a more stable market by providing liquidity and enhancing price discovery but also include mechanisms to resist and identify malicious attempts to manipulate market predictions.

Subsequent sections delve into specific ML algorithms that have made notable academic contributions and consequently have significant implications in using ML in HFT. Sarkar (2023) highlights Deep Q-Learning's effectiveness in enhancing profitability and risk-adjusted returns. Additionally, using Genetic Algorithms (GAs) with classifiers optimizes decision-making and adapts dynamically to market changes, increasing trading strategy precision and speed (Arifovic et al., 2022). Both Deep Q-Learning and GA’s with classifiers have evidence of supporting market stability through improved statistical arbitrage and efficient price discovery. Furthermore, advancements in defending against adversarial attacks, such as those by Ding et al. (2019) employing non-differentiable elements like random forests in DNNs, demonstrate increased security and accuracy of trading models.

3.1 Deep Q-Learning Algorithm

Deep Q-learning is a model-free RL algorithm combined with deep neural networks to assist an agent, like an HFT algorithm, in making decisions based on a reward objective (Massahi & Mahootchi, 2024). Sarkar (2023) utilises Deep Q-Learning to trade statistical arbitrage opportunities in an HFT context and concludes that profitability and risk-adjusted returns are enhanced with Deep Q-Learning. Pivotal techniques in Deep Q-Learning, such as Experience Replay, are emphasised due to its adeptness in maintaining stability and efficiency in the training phase of the model as it contributes significantly to the model's success. As Experience Replay utilises random mini-batches in training, it was able to be extended into backtesting and creating simulations to measure its effectiveness robustly. Consequently, the enhanced profitability and risk-adjusted returns are empirical evidence of its effectiveness.

Furthermore, the study's design focuses on RL’s application in statistical arbitrage, a strategy that supports market stability by providing liquidity and enhancing price discovery (Zaharudin et al., 2021). Moreover, it is a foundational strategy for hedge funds and other institutional firms (Morgan, 2013). Therefore, earlier concerns regarding RL can be dispelled in this case as RL augments an HFT strategy that is beneficial to market stability.

Furthermore, the study methodology is robust, demonstrated by extensive simulations and historical backtests. The study design supports the conclusion that RL is a pivotal tool in HFT trading in the context of statistical arbitrage, however would benefit from explicitly detailing the success they claim to have.

Nonetheless, conclusions and techniques by Sarkar (2023) align with preceding literature such as Chakole & Kurhekar (2019) and Ning et al. (2021). Experience replay, a technique within Deep Q-Learning that was emphasised by Sarkar (2023), was established in previous literature with robust evidence concluding that it enhances algorithm results (Ning et al., 2021). Alignment with earlier studies further reinforces RL's place in the HFT landscape and suggests that it can be applied in HFT.

3.2 Classifier System with Genetic Algorithm

Genetic algorithms (GA) optimise methods to find the most optimal solution given an objective (Pham-Toan & Vo-Van, 2023), and its versatility has demonstrated comprehensive predictive capabilities in HFT when augmented with classifiers. Arifovic et al., (2022) utilises this combination by employing a hybrid model where the GA continuously evolved according to a set of given trading objectives within a classifier system that continuously adapted to changing market dynamics.

Arifovic et al. (2022) demonstrate the adaptability of GA classifiers in HFT by evolving trading strategies in response to changing market dynamics. These classifiers adjust trading decisions based on real-time market data, enhancing the ability to exploit market inefficiencies effectively. The study underscores the classifiers' role in enhancing trade precision and minimizing risks, which is critical in the fast-paced HFT environment.

Expanding on the efficacy of GA classifiers, Arifovic et al. (2022) illustrate that enhancements in trading speed can significantly increase price efficiency and thus market stability. For example, when trading speeds are optimized, information efficiency improved by approximately 15% compared to baseline measures, consequently increasing price efficiency. However, the study does not fully address the scenarios under extreme market volatility, which limits the generalizability of these findings. Consequently, while GA classifiers demonstrate substantial benefits in controlled settings, their performance in unpredictable market conditions remains underexplored.

Overall, Arifovic et al. (2022) demonstrate GA Classifiers' applicability in HFT positively and contribute to market stability, albeit highlighting the risks associated with high-volatility periods within HFT. Specific investigations into this are warranted, but nevertheless other studies demonstrate the effective use of GA classifiers in HFT (Fu et al., 2024; Ntakaris et al., 2020). These studies came to a similar conclusion that GA's accompanied by classifiers are powerful predictive tools, thus reinforcing its case for its application in HFT.

3.3 Deep Learning Detection Algorithms

Adversarial attacks pose significant challenges to the robustness of Deep Neural Networks (DNNs), which is a critical subject in HFT (Ding et al., 2019). Recent advancements highlight the susceptibility of DNNs to such attacks, often due to the gradient-based manipulations that exploit network vulnerabilities (Chen et al., 2019). These adversarial examples are crafted to be indistinguishable from genuine data, leading to flawed model predictions and posing a threat to a models integrity.

Ding et al. (2019) proposes ahybrid model integrating non-differentiable random forests with deep neural networks (DNNs) to enhance security against adversarial attacks. Their approach leverages the inherent non-differentiability of random forests to block gradient access, which is a critical vulnerability in traditional DNNs. This integration not only thwarts a significant range of adversarial strategies on challenging datasets like CIFAR-10 and MNIST but also maintains classification accuracy on par with conventional DNNs, demonstrating the practicality of this method in preserving system performance while boosting defense mechanisms.

While Ding et al. (2019) demonstrates the effectiveness of their hybrid model in blocking adversarial attacks and maintaining accuracy, they do not fully address its computational efficiency. The potential impact on computational demand, crucial for real-time applications, remains unexamined. While it may be argued that further research is needed to assess whether the model's enhanced security can be efficiently implemented in HFT, the use of random forests being integrated with DNNs to enhance security against adversarial attacks is established.

Furthermore, Chen et al. (2019) extends the discussion to tree-based ML models, which have been underexplored in terms of adversarial robustness. They develop an algorithm that optimizes tree-based models against worst-case adversarial perturbations. By incorporating a max-min saddle point problem into the decision tree training, they find enhanced robustness of these models evidenced by larger and more sophisticated adversarial attacks, to mislead the model. Additionally, they maintained higher test accuracy even under adversarial conditions. Thus, academic evidence in tree-based ML models is established as a robust option for detecting adversarial attacks. Consequently, more research should be focused on this application, specifically for HFT.

Additionally, Gao (2021) critiques the efficacy of conventional two-sample tests like the Maximum Mean Discrepancy (MMD) in distinguishing between natural and adversarial datasets. An MMD test is enhanced with a deep learning kernel to create a more flexible and robust test called a SAMMD (Semantic-aware MMD). As the SAMMD empirically showed fewer Type 1 errors and a higher rate of correctly classifying adversarial attacks compared to

MMD, Gao (2021) sets the precedent for using this approach in detecting adversarial attacks in HFT. As a result, further research is necessary to confirm its usefulness in HFT.

4. Conclusion

This review critically evaluated the application of Machine Learning (ML) in High-Frequency Trading (HFT), focusing on its capabilities despite its inherent 'black box' nature, as evidenced by recent, peer-reviewed literature. The analysis highlighted the sophisticated mathematical models that underpin ML, enabling the capture of complex, non-linear relationships and efficient data processing essential in the rapid realm of HFT. However, concerns about the opacity and complexity of ML models were also discussed, particularly their implications for market stability and vulnerability to adversarial attacks. It was found that while advancements such as Deep Q-Learning and Genetic Algorithms contribute positively to market stability and trading strategy robustness, the full potential of ML in HFT is yet to be fully realized. Future research should aim to enhance the transparency of these models and develop more sophisticated methods to mitigate the risks of adversarial attacks, ensuring that ML applications in HFT can be both powerful and secure. This continued exploration is essential for harnessing ML's full potential in improving market mechanisms and safeguarding against the evolving landscape of cyber threats.

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