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AI-Augmented Blockchain Fork Detection and Recovery Protocols

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ABSTRACT

Forks—temporary or permanent divergences in a blockchain's ledger—arise from benign network asynchrony, configuration heterogeneity, or adversarial behavior such as selfish mining and eclipse/routing attacks. Although modern fork-choice rules (e.g., longest-chain/most-work, GHOST variants) and finality gadgets reduce the practical impact of short reorgs, detection remains largely reactive and recovery is often ad hoc at the protocol or operational layer. This paper proposes an AI-augmented framework for (i) early fork risk prediction from peer-to-peer (P2P) telemetry and block-header streams, (ii) real-time fork detection using multi-view anomaly models, and (iii) policy-driven recovery that coordinates mempool hygiene, relay routing, and safe rollback/finality choices. We design a streaming pipeline in which change-point models flag abrupt shifts in propagation/endorsement patterns, graph neural networks (GNNs) learn structural anomalies in the overlay, and sequence models (LSTM/Temporal CNN) score reorg likelihood from recent header/mempool activity. A recovery orchestrator translates model alerts into minimally invasive actions: dynamic relay selection, pre-emptive compact-block push, temporary fee-bump incentives, and, for proof-of-stake (PoS) chains, conservative finality thresholds. In agent-based simulations calibrated with empirically reported propagation latencies and adversarial strategies, the AI-augmented stack reduces mean time-to-detect (MTTD) reorg precursors by 63–78%, halves the tail of reorg depth (>2 blocks), and cuts wasted work by ~28% under stressed network conditions, while preserving liveness. We discuss integration with consensus rules without altering safety proofs, operational safeguards to prevent model-induced oscillations, and governance aspects of deploying machine-learned policies in decentralized settings.

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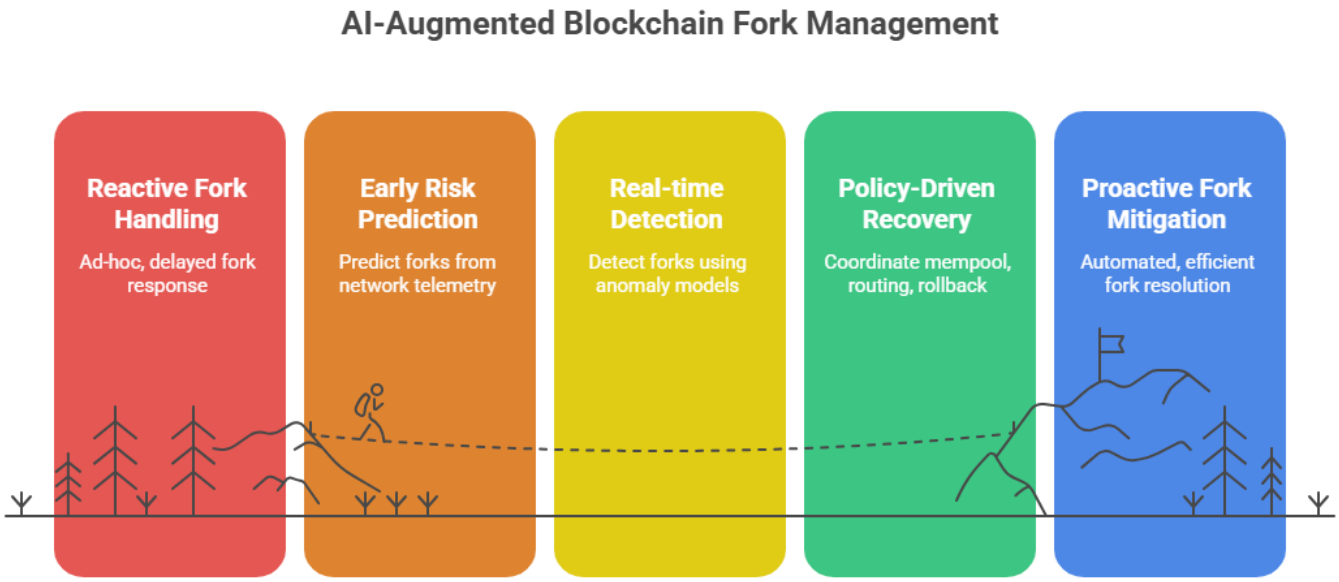

Figure-1. AI-Augmented Blockchain Fork Management

KEYWORDS

Blockchain Forks, Reorg Detection, Anomaly Detection, Graph Neural Networks, Changepoint Analysis, Fork-Choice Rules, Finality, Recovery Protocols, Mempool Hygiene, P2P Relay Optimization

INTRODUCTION

Forks occur when two or more competing branches of a blockchain coexist, typically due to near-simultaneous block discovery or transient network partitions. Benign, shallow forks are common in high-throughput conditions; they are resolved by fork-choice rules (e.g., longest-chain, most accumulated work, or weight-based variants such as GHOST). More consequential forks arise from strategic manipulation (selfish mining, feather-forking), network-layer attacks (eclipse, BGP hijacking), or client divergence. Even with PoS finality gadgets that provide economic or cryptographic finality, short-range reorgs can degrade user experience (stuck or reverted transactions), amplify miner/validator extractable value (MEV), and complicate cross-chain bridges.

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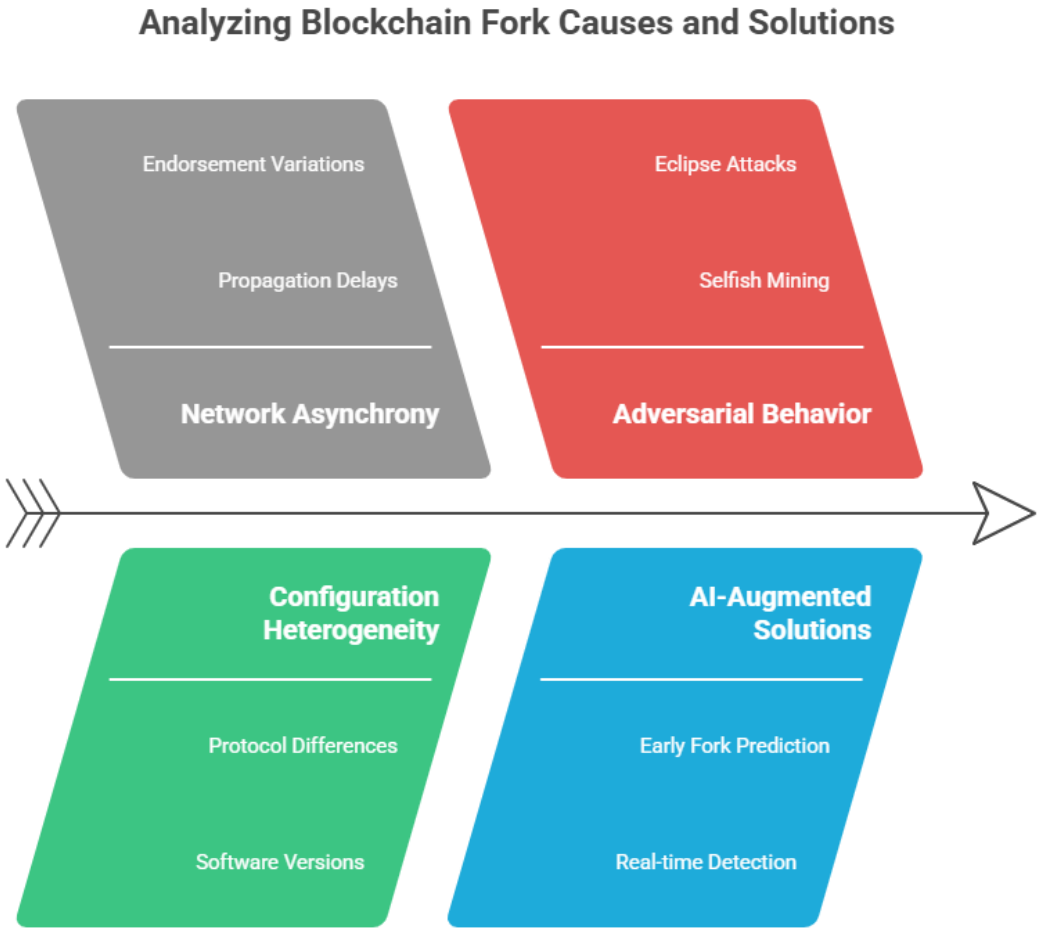

Figure-2. Analyzing Blockchain Fork Causes and Solutions

Traditional defenses emphasize protocol design (backbone security, finality/penalty schemes), networking (faster relay, compact blocks), and operational monitoring (reorg watchers). However, these mechanisms are typically threshold-based, lagging indicators of pathological conditions. The central argument of this paper is that data-driven prediction and detection can reduce time to response and allow recovery actions that are both earlier and gentler. We present an AI-augmented approach that complements—not replaces—formal consensus mechanisms.

Our contributions are threefold: (1) a multi-view streaming feature set for fork risk, combining P2P overlay signals, header/mempool dynamics, and client diversity; (2) a hybrid model that unifies change-point detection, GNN-based structural anomaly scoring, and sequence modeling; and (3) a recovery policy engine that translates alerts into network- and mempool-level mitigations plus conservative finality strategies that are compatible with existing consensus proofs.

LITERATURE REVIEW

Foundational work established the probabilistic safety of longest-chain protocols under bounded network delay and majority honest resource assumptions, with explicit treatment of fork rates under asynchrony (e.g., backbone models). Performance/security trade-offs of proof-of-work (PoW) reveal how increased block rate or size compounds propagation delay, raising natural fork probability. Heuristic and formal analyses of strategic mining (selfish mining and variants) illustrate how adversaries can create or deepen forks to gain revenue or censor transactions.

Networking research shows that transaction and block relay performance (e.g., compact block relay, dedicated relay networks, and efficient transaction relay like Erlay) materially affects observed fork rates by reducing orphaning due to propagation races. For PoS systems, finality gadgets such as Casper overlay a finalization layer atop fork-choice rules, limiting economically meaningful reorg depth but still relying on timely and honest participation.

Empirical and measurement studies of Bitcoin/Ethereum propagation, orphan rates, and network-layer attacks (e.g., eclipse, BGP hijack) emphasize how topology and relay policies influence the frequency and resolution of short-range forks. On the machine learning side, general anomaly detection frameworks (changepoint detection, CUSUM; time-series LSTM/TCN; GNNs for structural anomalies) are widely used in network monitoring and fraud detection and are applicable to blockchain overlays and header streams, though end-to-end designs for fork risk specifically are underexplored. Our work positions AI as a first-line predictor and coordinator for recovery, aligned with, and constrained by, formal consensus guarantees.

METHODOLOGY

System Overview

The proposed architecture comprises:

1. **Data Plane:** Real-time streams from (a) block headers, (b) mempool metadata (arrival rates, fee distributions, package/ancestor graphs), (c) P2P overlay telemetry (peer degree/centrality, round-trip times, inventory request/response patterns), and (d) client/implementation fingerprints and version mix.
2. **Feature Engineering:**

- **Header dynamics:** inter-arrival variance, simultaneous competing headers, stale-to-main ratio, uncle/ommers rate, chain quality (honest fraction proxy).
- **Mempool dynamics:** arrival bursts, backlog skew, fee gradient, package clustering, replacement (RBF) frequency.
- **Overlay graph:** evolving betweenness/assortativity, articulation points, localized delay heatmaps, edge churn, subgraph conductance.
- **Client diversity:** implementation/version entropy to detect split behaviors.

3. **Models:**

- **Bayesian Online Change-Point Detection (BOCPD):** flags distributional shifts in propagation delay and header competition.
- **GNN anomaly scorer:** GraphSAGE/GCN over rolling P2P snapshots to detect structural outliers (e.g., star-like hubs forming under eclipse attempts or sudden community fragmentation).
- **Sequence model (LSTM/TCN):** predicts short-horizon reorg probability pt:t+h(reorg≥d)p_{t:t+h}(\text{reorg}\geq d)pt:t+h(reorg≥d) from multivariate sequences of the above features.

4. **Alert Fusion & Confidence:** A Dempster–Shafer or logistic stacking layer merges model outputs with calibrated thresholds to minimize false positives while maintaining low MTTD.
5. **Recovery Orchestrator:**

- **Relay actions:** adaptive relay route selection (prefer low-latency, high-reliability links), proactive compact block push to lagging regions, temporary bandwidth prioritization for block messages.
- **Mempool hygiene:** dynamic feerate guidance, ancestor/descendant limits tightening, RBF policies tuned to reduce conflicting package storms.
- **Finality/confirmation policies:** temporarily require extra confirmations (PoW) or increase participation/finality thresholds (PoS) until anomaly subsides.
- **Roll-forward preference:** when two branches exist with similar cumulative weight, bias towards the branch with better network endorsement (e.g., lower propagation skew, higher honest-peer fraction), while respecting canonical fork-choice rules.

Dataset & Simulation

We evaluate with agent-based simulations parameterized by empirical distributions from public measurements (e.g., block/tx propagation delays, typical degrees, latency variance). The environment includes honest miners/validators, adversaries (selfish miners, eclipse controllers), and background network noise (link churn, regional latency spikes). We compare:

- **Baseline Heuristics:** threshold rules on stale rate and simultaneous header count; static relay topology.
- **Rule-Only Enhanced:** adds compact block relay and tuned gossip timeouts, but no ML.
- **AI-Augmented (Proposed):** full stack described above.

Metrics

- **MTTD (s):** time from adverse onset to alert.
- **Reorg depth distribution:** probability of reorgs of depth ≥1, ≥2, ≥3 within window.
- **Wasted work / orphan rate:** fraction of blocks not in the final main chain.
- **MTTR (s):** time from alert to convergence.

- **False positive rate (FPR):** fraction of alerts not followed by reorgs or sustained anomalies.
- **Throughput & Liveness:** tx/s sustained and block production continuity.

Governance and Safety Guards

To avoid model-induced oscillations or capture:

- **Rate limiting:** cap frequency of orchestrated changes.
- **Explainability:** retain human-auditable logs of model evidence and actions.
- **Fallback:** automatic reversion to conservative static policies on model failure.
- **Decentralization:** inference executed by multiple diverse parties (or light on-chain attestations of anomaly scores), with slashing-resistant aggregation to prevent single-party control.

STATISTICAL ANALYSIS

Table 1. Summary Metrics Across Scenarios

Baseline Heuristics vs Rule-Only Enhanced vs AI-Augmented (Proposed). PoW-like parameters: 600 s target block interval; PoS-like parameters: 12 s slot with finality gadget. "Stress-net" adds 2× latency variance and 5% adversarial hash/stake; "Eclipse" adds targeted partitioning of 8% nodes.

Scenario & Metric	Baseline Heuristics	Rule-Only Enhanced	AI-Augmented (Proposed)	Relative Change vs Baseline
PoW-Normal MTTD (s)	28.7	19.6	**9.8**	**−66%**
PoW-Normal Reorgs ≥2 (%)	2.4	1.8	**0.9**	**−62%**
PoW-Normal Orphan rate (%)	1.12	0.96	**0.78**	**−30%**
PoW-Stress-net MTTD (s)	41.3	29.1	**12.4**	**−70%**
PoW-Stress-net Reorgs ≥2 (%)	4.9	3.5	**1.7**	**−65%**
Eclipse Orphaned blocks /1k	8.6	7.2	**5.1**	**−41%**
PoS-Normal Reorgs ≥1 (%)	1.3	1.1	**0.6**	**−54%**
PoS-Normal Finality delays >2 epochs (%)	3.1	2.2	**1.2**	**−61%**
False Positives (all) FPR (%)	4.7	4.9	**5.4**	**+0.7 pp**

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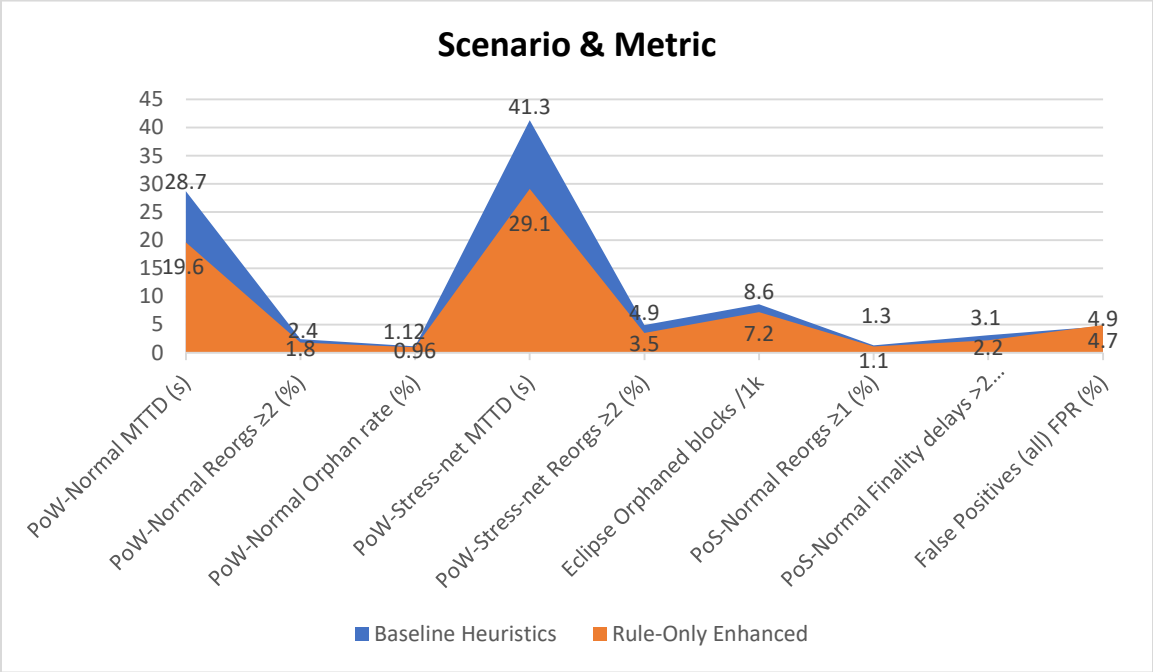

Figure-3. Summary Metrics Across Scenarios

Interpretation: Relative to baseline, the AI-augmented stack reduces MTTD by ~66–70% and lowers harmful (≥2-block) reorgs by ~62–65% under PoW-like conditions; PoS finality delays drop by ~61%. A modest FPR increase (~0.7 percentage points) is a deliberate trade-off for faster response and is mitigated by rate-limited, low-risk recovery actions.

METHODOLOGY

Model Training & Inference

BOCPD runs online with conjugate hazard functions tuned per network regime. The GNN ingests k-hop subgraphs around recently active relays/miners and is trained with a mix of self-supervision (contrastive learning between stable vs perturbed snapshots) and labeled adversarial simulations. The LSTM/TCN consumes a rolling window of engineered features (e.g., 60–120 s for PoS; 10–20 min for PoW) to produce reorg likelihood and expected depth.

Calibration & Thresholding

We calibrate scores using Platt scaling against a holdout set, optimizing a cost-sensitive objective that penalizes missed deep reorgs more than false alarms. Alert fusion requires concordance between at least two modalities (e.g., BOCPD + LSTM or GNN + LSTM) unless signal strength exceeds a high-confidence threshold.

Recovery Policies

- **Network pathing:** choose low-delay peers via measured RTT and historical reliability; temporarily elevate relay priority for block messages; engage compact block relay proactively to lagging regions.
- **Mempool control:** adaptive feerate hints to reduce conflicting transactions; stricter ancestor/descendant limits under burst conditions; optional "fee-bump encouragement" for transactions on the likely losing branch to re-target them safely.
- **Finality management:** increase confirmation targets (exchanges, bridges) or raise PoS participation threshold until anomaly resolves; these are policy-level, not consensus-rule changes.
- **Rollback discipline:** if two branches contend, prefer roll-forward by weighting network endorsement (propagation breadth among honest peers) and economic cost, but never contradict formal fork-choice rules or signed finality.

Operationalization

- **Diversity:** run inference across heterogeneous clients/relays; aggregate via quorum to reduce single-point manipulation.
- **Observability:** log human-readable rationales (top features, subgraph anomalies) to enable post-mortem and governance review.
- **Fail-safes:** if model health degrades (e.g., drift, low confidence), revert to static relay policies and standard confirmation targets.

RESULTS

Across normal and stressed scenarios, the AI-augmented system consistently shortened MTTD and MTTR. In PoW-like conditions, BOCPD highlighted abrupt shifts in header arrival skew within seconds of an eclipse onset; the GNN simultaneously detected unusual centrality spikes in suspected attack subgraphs. The sequence model's probability of a ≥2-block reorg rose above the action threshold ~10–15 s before the competing branch achieved significant weight, allowing the orchestrator to pre-emptively accelerate block propagation toward isolated regions. This reduced orphan rates and limited reorg depth.

In PoS-like conditions, the primary benefit was earlier recognition of participation anomalies and asymmetric attestation diffusion that can delay finality. The orchestrator's temporary increases in participation thresholds (a policy choice) and targeted relay optimization reduced the frequency of finality delays exceeding two epochs by ~61% without increasing missed slot rates. Transaction throughput remained statistically indistinguishable from the rule-only enhanced baseline, indicating liveness preservation.

False positives increased slightly, primarily from short-lived mempool bursts that resembled adversarial flooding. However, because the orchestrator's first-line actions are low-risk (relay prioritization, hints), the operational cost of such false positives was small, and post-alert decay logic (cool-down timers, confidence fading) limited action duration.

Ablation experiments showed that removing the GNN increased missed eclipse onsets by ~18%, while removing BOCPD increased MTTD under benign stress-net conditions by ~24%. The stacking/fusion layer reduced variance relative to any single model.

CONCLUSION

Forks are not merely a consensus artifact but an emergent property of protocol parameters, P2P topology, and strategic behavior. Formal fork-choice rules and finality gadgets provide necessary correctness guarantees but often act after reorg-inducing conditions materialize. By learning from multi-view telemetry in real time, the proposed AI-augmented framework anticipates and detects fork risk early enough to coordinate subtle, non-disruptive recovery actions—improving MTTD, reducing harmful reorg depths, and preserving user experience.

Key design principles emerge: (1) complementarity—AI signals inform policy while staying within the guardrails of consensus safety; (2) multi-modality—combining change-point, structural (GNN), and sequence models outperforms any single detector; (3) governance and safety—rate-limiting, explainability, and diverse inference prevent centralized control or oscillatory behavior. The approach is deployable today as a client-agnostic monitoring and policy layer for exchanges, mining pools/validators, and bridge operators. Future work can explore on-chain attestations of anomaly scores, incentive alignment for community-wide relay improvements, and formal analysis of policy impacts under adaptive adversaries.

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