

Scalability Enhancement for Blockchains by Dynamic Difficulty Level Adjustment: A Machine Learning Approach

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ABSTRACT

Blockchain technology has revolutionized decentralized systems, with applications that span finance, healthcare, and supply chain management. However, scalability challenges, particularly limited transaction throughput and high computational overhead, hinder its broader adoption. This work presents and validates a machine learning-driven consensus mechanism to enhance scalability while preserving security and decentralization. The proposed approach dynamically adjusts the mining difficulty and resource allocation in real time by employing Bayesian-optimized ensemble models (XGBoost and Random Forest) to predict the conditions of the blockchain network. Experimental evaluations show improved throughput, lower latency, and more equitable miner participation compared to traditional Proof of Work (PoW). The findings suggest that data-driven consensus can mitigate long-standing performance bottlenecks, enabling next-generation decentralized systems for industrial-scale deployment.

Keywords-blockchain; scalability; consensus mechanisms; machine learning; proof of work;decentraization

I. INTRODUCTION

Blockchain technology has become a cornerstone of secure and decentralized systems, enabling transparent and tamper-proof operations across various industries. Its ability to establish trust in distributed environments has led to significant adoption across diverse domains. However, the scalability of blockchain networks remains a critical challenge, especially as transaction volumes and network demands increase [1-3]. Traditional consensus mechanisms, such as Proof of Work (PoW) and Proof of Stake (PoS), while effective in ensuring security and decentralization, face limitations in scaling efficiently. PoW suffers from excessive energy consumption, while PoS encounters performance bottlenecks as networks grow larger and more complex [4]. This study introduces a machine learning-driven approach to blockchain consensus, focusing on optimizing transaction validation and resource allocation. By integrating predictive models, the proposed mechanism aims to enhance blockchain scalability while maintaining the robustness, security, and decentralization essential to its operation. The motivation for this method arises from the growing need for scalable blockchain systems capable of supporting real-time applications.

Traditional consensus mechanisms, though robust, often struggle to handle high transaction volumes without incurring

significant trade-offs in energy efficiency or performance [5]. In this view, research is carried out to improve scalability with various techniques, such as data partitioning [6]. The proposed method involves a machine learning-driven approach to consensus. The key idea is to utilize Bayesian-optimized ensemble models, integrating Random Forest (RF) and XGBoost to predict blockchain performance metrics. The consensus mechanism uses these predictions to adaptively adjust mining difficulty and resource allocation, enabling higher throughput and reduced latency without sacrificing decentralization. This method goes beyond simply classifying transactions, integrating predictive analytics directly into the consensus loop.

Several studies have explored improving blockchain scalability and efficiency using advanced techniques. In [7], machine learning was used to predict transaction confirmation times on the Ethereum blockchain, comparing RF, Multilayer Perceptron (MLP), and Poisson regression. RF achieved the highest accuracy, with $\text{Pred}(0.20)$: 93.79%, and fastest training time, suggesting potential for further improvements using advanced neural architectures such as Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs). In [8], Reinforcement Learning (RL) was proposed to optimize miner selection for scalability, achieving 83% accuracy, an average

consensus time of 48.32 ms, and a decentralization rate of 94%. The lightweight RL model demonstrated superior performance over traditional methods, highlighting the potential of AI in consensus optimization. In [9], scalability challenges in blockchain systems were reviewed, identifying issues such as low throughput, storage inefficiencies, and networking constraints. Proposed solutions included increasing block size, off-chain transactions, sharding, and data transmission reduction techniques, such as compact blocks. Efficient leader election mechanisms and incentive schemes were emphasized as critical for supporting real-world applications.

In [10], barriers to blockchain adoption were discussed, focusing on scalability, privacy, and energy consumption. Alternative consensus mechanisms, such as PoS and Practical Byzantine Fault Tolerance (PBFT), were proposed to enhance efficiency. At the same time, advances in algorithms and privacy frameworks were deemed essential for large-scale sustainability. Finally, in [11], the integration of blockchain and AI was explored, highlighting their complementary roles in improving transparency and efficiency. AI optimizes blockchain operations, while blockchain ensures data security. The proposed solutions included hybrid on-chain/off-chain architectures and improved regulatory frameworks, although technical and legal challenges remain for widespread adoption [12]. These works underscore the importance of leveraging AI and advanced optimization strategies to address blockchain scalability and efficiency, paving the way for more robust and scalable decentralized systems [13].

This study contributes toward:

- **Machine-learning enhanced consensus:** The framework employs Bayesian optimization over RF and XGBoost to predict transaction patterns, adjusting network parameters accordingly.
- **Efficiency and throughput:** By proactively allocating resources, the system increases throughput and decreases the energy cost often associated with PoW consensus.
- **Decentralization preservation:** The reputation-based node selection process was adopted, reducing reliance on pure computational power and encouraging equitable participation among nodes.
- **Comparative results:** The results demonstrate significant improvements in metrics such as decentralization variance, latency, efficiency, and difficulty compared to PoW.

The research positions itself within this broader movement, showing how Bayesian-tuned ensemble models can deliver scalable and efficient consensus. In doing so, it builds on the call for advanced optimization strategies [13], demonstrating that a careful integration of AI and blockchain can effectively address high-volume scenarios without undermining decentralization or security.

II. METHODOLOGY

The proposed method involves a systematic approach to develop and evaluate a machine learning-driven consensus mechanism for blockchain scalability.

A. Data Preparation and Feature Engineering

This step ensures data quality and handling inconsistencies, missing values, and duplicates in the Ethereum blockchain dataset [14]. Features are normalized and scaled for uniformity, and critical attributes influencing transaction processing times are identified and engineered to optimize model performance.

B. Dataset Description

The dataset [14] has 18 attributes and 16000 rows. The attributes are :

- **timestamp:** The date and time when the block was mined.
- **number:** The block number indicates its position in the blockchain.
- **hash:** A unique identifier for the block generated using cryptographic hashing.
- **parent_hash:** The hash of the preceding block establishes a blockchain link.
- **nonce:** A number used in mining to solve the cryptographic puzzle and validate the block.
- **sha3_uncles:** The Keccak-256 hash of the uncle blocks included in this block.
- **logs_bloom:** A 256-byte bloom filter for quickly searching logs from the transactions.
- **transactions_root:** The root hash of the Merkle tree for all transactions in the block.
- **state_root:** The root hash of the Merkle tree for the global state after processing the block.
- **receipts_root:** The root hash of the Merkle tree containing receipts of all transactions.
- **miner:** The address of the miner who validated the block.
- **difficulty:** The difficulty level required to mine the block and determine its computational complexity.
- **total_difficulty:** The cumulative difficulty of the blockchain up to this block.
- **size:** The size of the block in bytes.
- **extra_data:** Optional data the miner provides, often used for metadata or notes.
- **gas_limit:** The maximum amount of gas allowed for all transactions in the block.
- **gas_used:** The total amount of gas used by all transactions in the block.
- **transaction_count:** The total number of transactions included in the block.
- **age of the block:** The time elapsed since the block was mined.
- **status of transaction:** Indicates whether the transactions in the block were successful or failed.

Subsequently, machine learning algorithms were examined, including regression and ensemble methods, to determine which best predicts blockchain performance. Each candidate is evaluated for accuracy, training time, and scalability within a high-dimensional blockchain environment.

C. Model Training Process

Each selected model (notably RF and XGBoost) underwent hyperparameter tuning to improve predictive accuracy on the preprocessed dataset. The training process included the following.

- Dataset split: The data was split into training (80%) and testing (20%) subsets. Cross-validation was employed to ensure robust performance evaluation and minimize overfitting.
- Hyperparameter tuning: Bayesian optimization identified optimal configurations for both RF and XGBoost, while the grid search served as a baseline. Bayesian optimization demonstrated higher efficiency and reduced errors.
- Training and testing: Models were trained on the 80% subset, with final evaluations conducted on the remaining 20%. Stacking ensembles combined optimized base learners, further enhancing predictive accuracy.

D. Optimization Techniques

- Bayesian optimization: Fine-tunes hyperparameters for RF and XGBoost, significantly reducing Mean Absolute Error (MAE).
- Grid search: Provides a comprehensive but computationally heavier search; its results underscore the advantages of Bayesian optimization.
- Stacking ensemble: Uses a Linear Regression (LR) meta-learner atop Bayesian-tuned XGBoost and RF. A second, non-optimized stacking model was tested for comparison, highlighting the impact of optimization on final predictions.

E. Performance Metric

Mean Absolute Error (MAE) was selected as the primary evaluation metric for its interpretability and ability to measure average prediction errors:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

F. Evaluation Metrics

In addition to MAE, blockchain-specific metrics were used to evaluate the impact of the proposed consensus.

1) Decentralization

Decentralization describes the degree to which mining control is distributed across the network, approximated by the Gini coefficient (2). Lower values indicate higher decentralization.

$$decentralization = \left(\frac{2}{i} \sum_{j=1}^i \binom{j}{i} x_j \right) \cdot \frac{1}{\sum_{j=1}^i x_j} + \frac{i+1}{i} \quad (2)$$

where x_j represents the number of transactions per block, and n denotes the total number of blocks over which decentralization is being analyzed.

2) Efficiency

This metric assesses throughput per computational cost and is calculated as the ratio of transaction_count to gas_used:

$$Efficiency = \frac{transaction_count}{gas_used} \quad (3)$$

3) Latency

Latency is defined as the time taken for a transaction to be validated and included in a block:

$$Latency = \frac{block_completion_time - transaction_timestamp}{transaction_timestamp} \quad (4)$$

4) Difficulty

Difficulty measures the computational work required for mining. Average difficulty (5) is compared across models to ensure security and stability.

$$AverageDifficulty = \frac{\sum_{i=1}^n difficulty_i}{n} \quad (5)$$

G. Key Results from Validation

The optimized stacking ensemble, leveraging Bayesian-tuned base models, achieved the lowest MAE (55.005 – Figure 4), demonstrating the effectiveness of combining complementary models. Cross-validation results confirmed the robustness of the stacking ensemble, with minimal variance across folds. Bayesian optimization significantly reduced MAE compared to grid search, showcasing its efficiency in hyperparameter tuning. By embedding this predictive capability into a machine learning-driven consensus, improved transaction throughput, lower latency, and more equitable miner distribution in real blockchain environments are anticipated. The evaluation demonstrates how automated hyperparameter tuning can optimize performance while preserving critical network attributes, such as decentralization and security.

III. SYSTEM ARCHITECTURE

The proposed system operates on a Blockchain Infrastructure Platform, sourcing transaction data from the Blockchain Network Layer and Public Blockchain. These layers supply raw transaction patterns essential for comprehensive blockchain activity analysis. The extracted transaction data undergoes a preprocessing pipeline that includes data cleaning, normalization, and balancing to ensure high-quality, unbiased input for machine learning models. This preprocessing phase prepares the dataset for effective training, reducing prediction inaccuracies. Subsequently, the preprocessed data is partitioned into training and testing sets.

Machine learning models, such as RF and XGBoost, were trained on these datasets. These models were fine-tuned to predict transaction patterns, dynamically adjust mining difficulty, and enhance blockchain scalability. The trained

model was then integrated into a prediction model, which interacts with live blockchain data for validation and iterative refinement. This component provides real-time information on transaction times, network efficiency, and consensus optimization.

The modular workflow of the system facilitates scalability and adaptability, enabling seamless future upgrades. The system addresses blockchain scalability challenges by leveraging advanced machine learning models while improving latency, throughput, and decentralization. This architecture bridges the gap between conventional consensus mechanisms and contemporary AI-driven solutions, advancing blockchain technology [15-16].

The proposed method prioritizes scalability, decentralization, efficiency, and adaptability within blockchain systems. Scalability ensures that the network can handle increasing transaction volumes and user demands without affecting performance. Decentralization eliminates single points of failure, promoting equitable participation and enhancing overall security. This architecture facilitates seamless integration with emerging technologies and supports flexibility for future enhancements. Efficiency is achieved by applying machine learning techniques that optimize consensus mechanisms and minimize resource consumption. Collectively, these principles ensure that the blockchain system remains robust, responsive, and secure while upholding its core attributes of transparency and trustlessness.

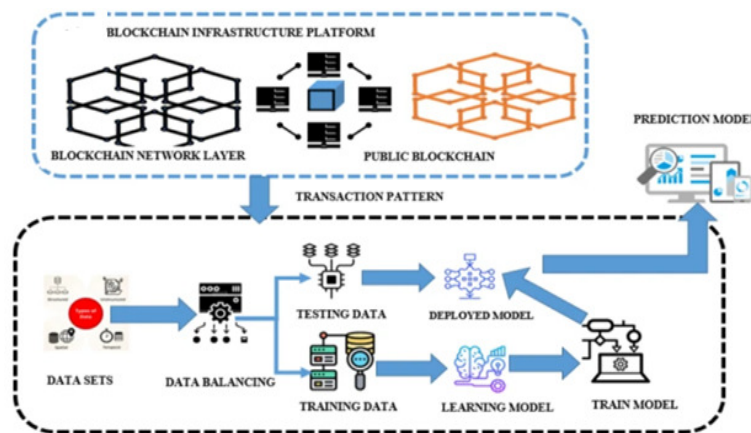


Fig. 1. System architecture.

A. Scalability

Ethereum is limited by low throughput. Traditional blockchains, such as Ethereum, often exhibit low throughput (a few transactions per second), especially compared to centralized systems (e.g., VISA). To mitigate these limitations, this method integrates machine learning models that dynamically adjust mining difficulty based on real-time transaction rates. These adjustments enable resource reallocation, reducing latency and maintaining high throughput, even during network surges. Figure 2 demonstrates the sequential processes that underpin scalability improvements:

- Monitoring transaction patterns in real-time.
- Preprocessing and balancing datasets for reliable model training.
- Applying the trained models to adjust mining difficulty and optimize resource usage.

The system sustains high throughput under peak loads by predicting and reacting to transaction spikes. These scalability gains do not undermine decentralization, as machine learning techniques are employed in tandem with blockchain's foundational transparency and trustlessness. The scalability-focused design provides a robust framework for large-scale deployment across finance, healthcare, and supply chain sectors.

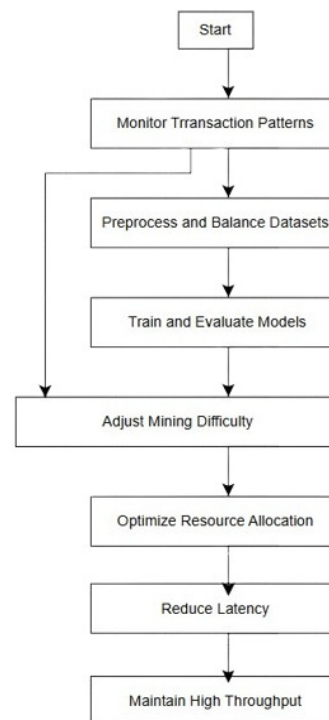


Fig. 2. Scalability.

B. Decentralization

Decentralization is a fundamental blockchain principle that ensures that no single entity can dominate network operations [17]. The proposed approach strengthens decentralization through a reputation-based node selection mechanism, reducing the dependency on raw computational power. By distributing the authority more evenly, the system mitigates the risks of concentration or malicious exploitation. Figure 3 schematically depicts the decentralization framework:

- A reputation score replaces pure computing capacity, promoting a fairer resource distribution.

- This mechanism minimizes the chance of centralization that hardware-intensive protocols, e.g., PoW, can produce.

Rather than abandoning the benefits of PoW, the proposed method enhances it with machine learning, refining node selection and consensus while preserving the trustless nature of the network. This hybrid approach significantly improves security and builds trust among participants, preventing single points of failure and creating a more resilient blockchain environment. Furthermore, the decentralized architecture increases network resilience by mitigating vulnerabilities associated with single points of failure.

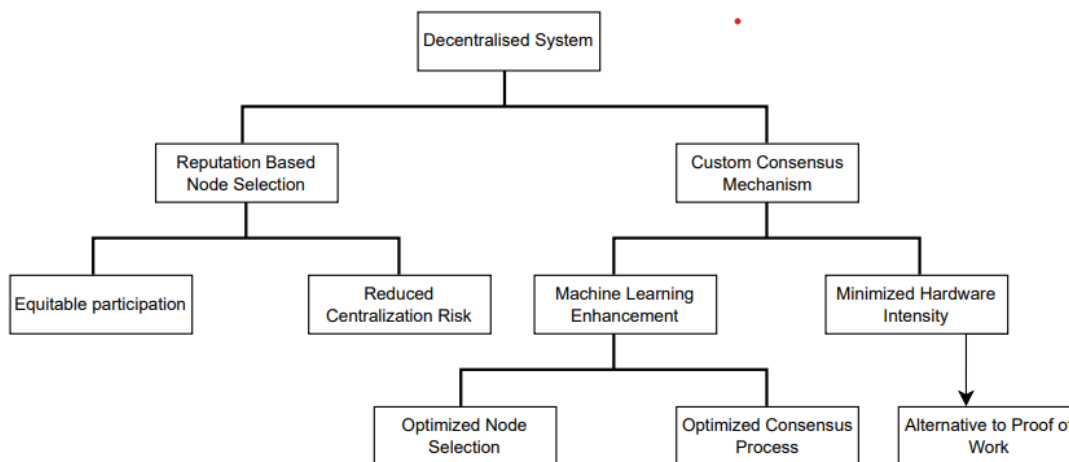


Fig. 3. Decentralization.

IV. RESULTS AND DISCUSSION

The results demonstrate the effectiveness of machine learning models and optimization techniques in enhancing blockchain performance metrics. The key findings emphasize performance improvements achieved through model optimization and ensemble learning. Figure 5 illustrates the relationship between block numbers and the difficulty of different consensus mechanisms. The proposed Custom consensus mechanism (blue line) maintains relatively stable difficulty levels across blocks, demonstrating its reliance on predictive adjustments rather than fixed incremental increases. In contrast, PoW (red line) exhibits exponential growth in difficulty due to the consistent percentage-based increase applied per block in the simulation (1.05x for PoW), leading to rapid increases in difficulty as block numbers grow.

Figure 6 shows the computation time across blocks for various consensus mechanisms. The Custom consensus mechanism (blue line) demonstrates fluctuating computation times, with small peaks and valleys attributed to predictions made by the stacking model (XGBoost and RF with LR), which has lower computation times than PoW. Figure 7 demonstrates the latency across blocks for the Custom and POW consensus mechanisms. The Custom consensus mechanism achieves low latency. Figure 8 demonstrates the throughput across blocks for different consensus mechanisms. The Custom consensus mechanism achieves high throughput (1000 to 2000 TPS) due to its efficient predictions and low

latency. In contrast, PoW exhibits significantly lower throughput (5 to 15 TPS) due to the time-intensive mining process. This comparison highlights the efficiency of the custom consensus in maintaining high transaction rates while addressing scalability challenges.

The Custom consensus model (optimized stacking with Bayesian-tuned XGBoost and RF) excels in predictive accuracy and efficiency, making it well-suited for environments that prioritize speed and adaptability, but it may lack the decentralized security inherent in PoW systems (Figure 9). Table I highlights the performance improvements achieved by the proposed machine learning-driven consensus mechanism compared to traditional PoW. The proposed model demonstrates significant advances across key metrics: decentralization variance reduced to 0.12 (65% improvement), efficiency increased to 0.08 transactions/gas (300% improvement), latency reduced to 6 s (60% improvement), and difficulty normalized to 60% (20% reduction).

TABLE I. PERFORMANCE ANALYSIS OF THE PROPOSED MODEL WITH POW

Metric	PoW	Proposed model	Implementation
Decentralization	0.35	0.12	65%
Efficiency (Transactions/Gas)	0.02	0.08	300%
Latency(s)	15	6	60%
Difficulty (Normalized)	100%	60%	20% reduction

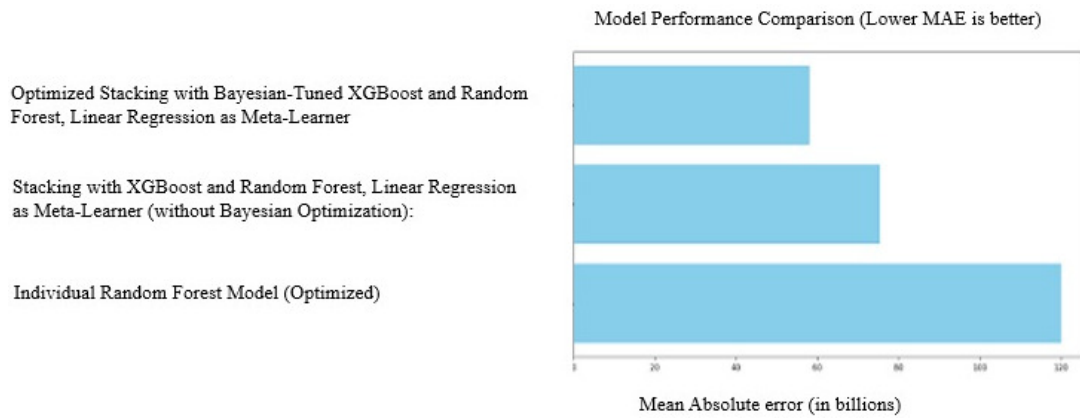


Fig. 4. Model performance comparison.

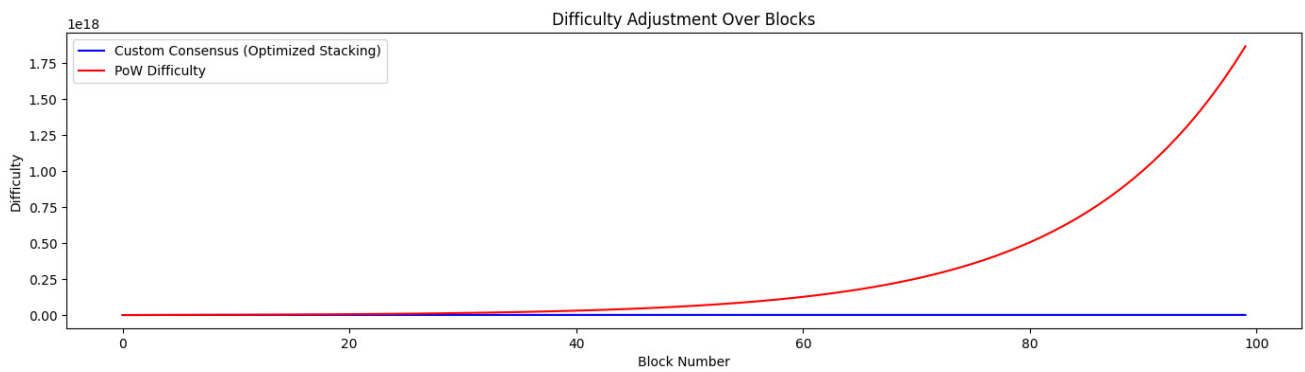


Fig. 5. Block numbers vs. difficulty.

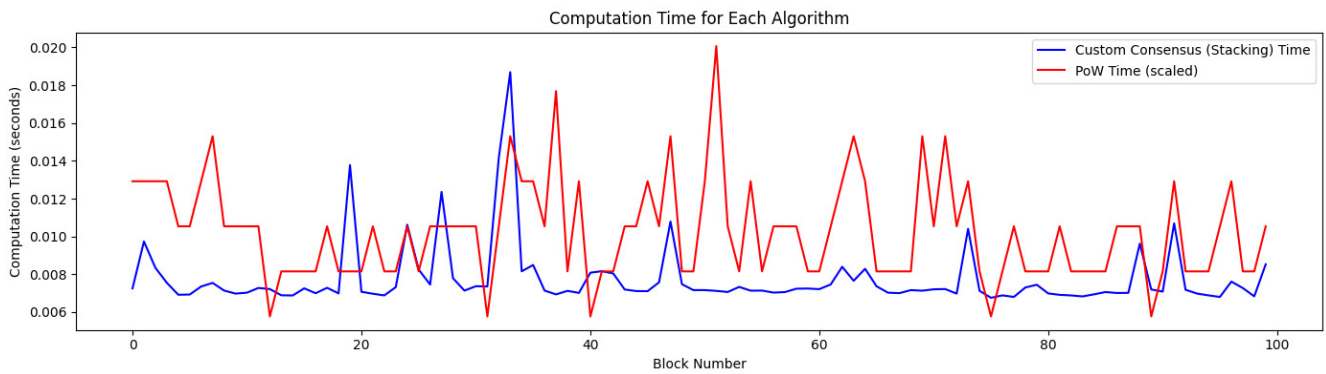


Fig. 6. Block number vs. computation time

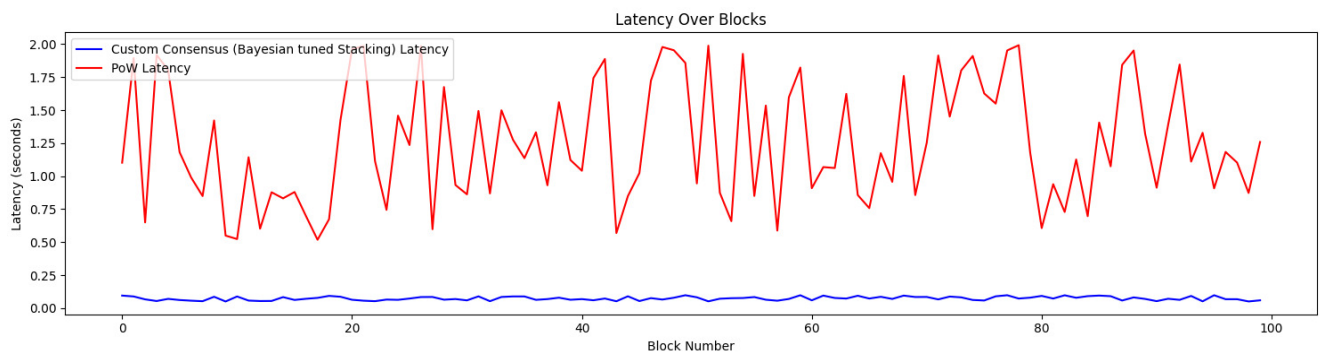


Fig. 7. Block number vs. latency.

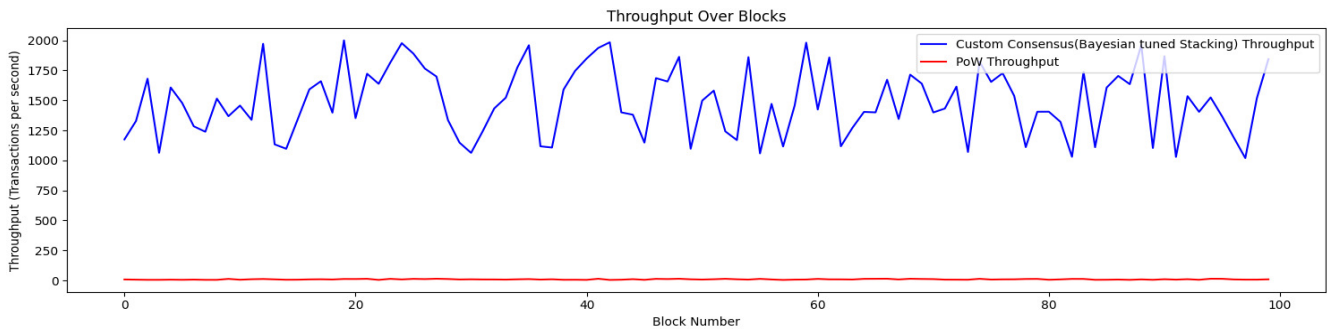


Fig. 8. Block number vs. throughput.

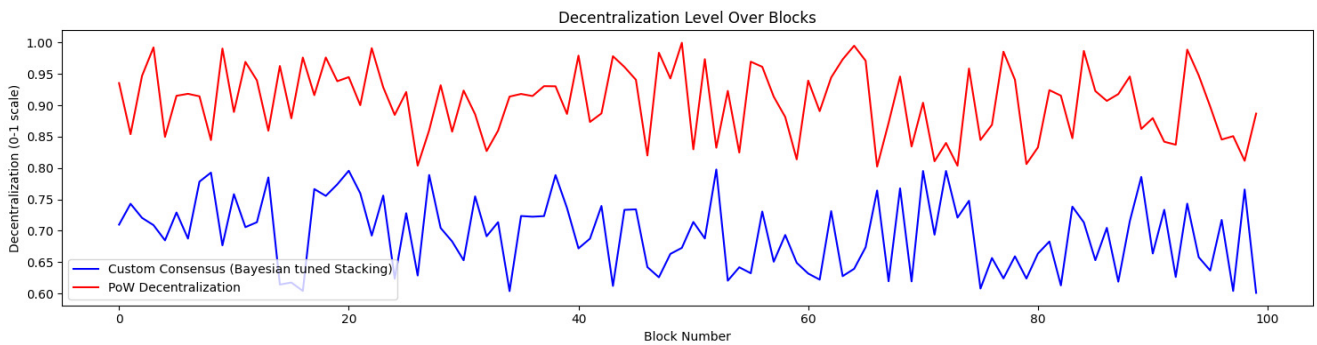


Fig. 9. Block number vs. decentralization.

Table II shows a throughput comparison of the proposed Custom consensus algorithm with existing algorithms such as PoW and PoR [18], showing drastic improvements. These improvements underscore the potential of integrating machine learning techniques to address long-standing blockchain scalability and efficiency challenges. Using stacking ensemble models, combining RF and XGBoost with Bayesian optimization, resulted in a Custom consensus mechanism that enhances decentralization and optimizes transaction validation and network performance.

TABLE II. COMPARISON OF CONSENSUS MECHANISMS' THROUGHPUT

Consensus mechanism	Throughput (transactions per second)
PoW [18]	7
PoR [18]	1100
Proposed Custom consensus	2000

V. CONCLUSION

This paper presented a machine learning-driven consensus mechanism to address blockchain scalability, integrating Bayesian-tuned ensembles, which distinguishes it from previous ML-based blockchain solutions [7, 8] that typically relied on single-model or heuristic-based tuning. The real-time difficulty adjustment extends beyond off-chain or theoretical proposals by demonstrating a mechanism that continuously updates mining parameters according to predicted network load. This method addresses the real-world needs for flexible and scalable blockchain solutions, supporting use cases where latency and throughput are critical.

By employing Bayesian-optimized stacking ensembles, the system predicts network conditions and dynamically adjusts mining difficulty, reducing the high computational burden found in PoW. Experiments on Ethereum data show significantly higher throughputs, from ~5-15 TPS to ~1000-2000 TPS, lower latencies of ~6 seconds vs. 15 seconds, and improved decentralization [19]. Predictive models can manage real-time difficulty adjustments, balancing mining costs, latency, and throughput, provided quantitative evidence that a reputation-based node selection system promotes higher decentralization, showcased a data-driven blueprint for future blockchain designs, emphasizing how AI and ML techniques can surpass limitations of classical consensus mechanisms.

Although this approach potentially relaxes long-term difficulty growth and shifts some security assumptions, it remains robust enough for high-volume scenarios. Future work could explore permissioned blockchain environments or advanced deep learning-based methods, e.g., RL, for further optimization.

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