A Scalable and Transparent Framework for Intelligent Social Media Moderation Using Blockchain and Federated Learning

Neeraj Sharma[1], Leeladhar Chourasiya[2], Mahavir A. Devmane[3], Bharti Bhattad[4], Medha Nitin Kulkarni[5], Vinod Sapkal[6], Dr Satyamangal Rege[7], Sushma Khatri[8]

[1] Department of Information Technology, Padmbhushan Vasantdada Patil Pratishthan's College of Engineering and Visual Arts, Mumbai-India; Email : nrjg0101@gmail.com
[2]Department of Computer Science and Engineering , Acropolis Institute of Technology and Research Indore, India; Email: mhowwala12@gmail.com
[3]Department of Computer Science and Engineering (AI&ML), Padmbhushan Vasantdada Patil Pratishthan's College of Engineering and Visual Arts, Mumbai-India; Email : dmahavir@gmail.com.
[4]Department of Computer Science and Engineering , Acropolis Institute of Technology and Research Indore, India; Email: bhartibhattad118@gmail.com
[5]Department of Information Technology, Padmbhushan Vasantdada Patil Pratishthan's College of Engineering and Visual Arts, Mumbai-India; Email : mnkulkarni75@gmail.com
[6]Department of Information Technology, Padmbhushan Vasantdada Patil Pratishthan's College of Engineering and Visual Arts, Mumbai-India; Email: vinodsapkal@pvppcoe.ac.in
[7]Dean Visual Arts Vasantdada Patil Prathisthan's College of Engineering and Visual Arts Mumbai-India; Email : satyamangalrege@gmail.com
[8]Department of Computer Science and Engineering, Acropolis Institute of Technology and Research Indore, India; Email: skhatri10@gmail.com

Abstract
With social media platforms like Facebook booming in recent years, we've seen a big rise in issues like misinformation, hate speech, and other harmful content that impact millions of users around the world. Traditional ways of moderating content just can't keep up with these challenges. They often fall short when it comes to being transparent, quick to respond, and scalable enough to handle everything. This paper introduces a fresh new approach that combines Blockchain, AI, and Machine Learning to tackle these problems head-on. The framework allows for real-time tracking and smart analysis, which helps to respond quickly to harmful activity on social media. By using blockchain to keep a permanent record of content, AI to understand the emotional tone and behavior behind posts, and machine learning to find patterns and spot unusual activities, this method presents a strong, decentralized solution to the moderation challenge. We back this up with a lot of data from Facebook, showing that this approach significantly improves our ability to spot and deal with threats on the spot while also making things clearer and boosting user trust.

1. Introduction

Social media platforms have become indispensable channels for communication, information sharing, and community engagement. However, the rapid expansion of these platforms—particularly Facebook, with its billions of users—has amplified challenges related to harmful content such as misinformation, hate speech, and fake news. Traditional content moderation systems, largely centralized and reactive, are increasingly inadequate in addressing these issues. They often lack transparency, making moderation decisions opaque and difficult to audit, and suffer from delays that allow harmful content to spread before intervention, thereby undermining user trust and platform credibility.

Existing approaches, which rely heavily on AI and machine learning, face notable limitations: their decision-making processes are often black boxes, prone to biases, and incapable of providing real-time responses at the scale required. This reactive nature hampers timely intervention, especially during crises or politically sensitive situations. Additionally, the absence of a transparent and verifiable record of moderation actions impairs accountability and the ability for users to challenge decisions.

In contrast, the proposed framework integrates blockchain technology with AI and ML to overcome these limitations. Blockchain provides a tamper-proof, transparent log of all moderation activities, fostering trust and accountability. AI-powered natural language processing and behavioral analysis enable rapid, context-aware detection of harmful content, facilitating immediate, autonomous responses. ML techniques continuously learn from evolving patterns, enhancing adaptability and precision.

The significance of this integrated system lies in its capability to enable **real-time, transparent moderation**—critical for effectively combating misinformation and harmful content in today's fast-paced social media environment. By ensuring that moderation actions are both prompt and auditable, the framework aims to significantly improve the

efficacy, fairness, and user trust in social media content governance. Although exemplified through a case study on Facebook, the architecture's scalability allows adaptation across diverse platforms, setting a new standard for ethical, responsible, and responsive social media moderation.

1.1 Current State of the Study:
Facebook has implemented various automated content moderation techniques using artificial intelligence (AI) and machine learning (ML), including real-time spam detection, hate speech classifiers, and fact-checking systems. These tools are supplemented by user reports and manual review teams. For instance, Facebook's AI models are designed to proactively detect 94.7% of hate speech before it is reported by users (Facebook Transparency Report, 2023). Additionally, Facebook employs multilingual NLP models and real-time behavioral analytics to handle content across regions and contexts (Gorwa, Binns, & Katzenbach, 2020).
Despite these advancements, studies and real-world incidents continue to highlight the limitations of these systems. The AI models used by Facebook operate largely within a centralized, proprietary framework. Researchers such as Narayanan et al. (2022) have pointed out that these AI systems often lack explainability and are prone to false positives, particularly in politically or culturally sensitive content. Moreover, Facebook's oversight board has cited instances where moderation lacked consistency and accountability, further diminishing user trust (Oversight Board, 2021).
Furthermore, it has been observed that Facebook's content moderation pipeline is reactive rather than proactive. The platform often fails to intercept coordinated disinformation campaigns or harmful viral content before it gains momentum (Guess et al., 2019). This gap between detection and intervention reduces the efficacy of its moderation infrastructure, especially during crises or political upheaval.
Collectively, these studies demonstrate the need for a transparent, auditable, and real-time system that can not only detect but also intelligently respond to harmful content on Facebook. This paper builds upon these insights by proposing a solution that integrates the advantages of blockchain for transparency, AI for content understanding, and ML for behavioral prediction and anomaly detection

1.2 Limitations of Existing Systems:
- **Centralized Infrastructure:** Existing moderation processes rely on centralized control, which not only introduces a single point of failure but also raises concerns about censorship and user autonomy.
- **Lack of Transparency and Auditability:** Users have minimal insight into how moderation decisions are made, and there is no publicly verifiable log of content that has been flagged or removed.
- **Delayed Intervention:** AI systems often operate on a reactive basis, flagging content only after it has caused harm or gained viral traction.
- **Algorithmic Bias:** ML models trained on biased data can perpetuate unfair treatment of certain groups, further undermining trust in automated moderation.
- **Scalability Challenges:** As content volume grows exponentially, even sophisticated systems struggle to maintain real-time responsiveness at scale.

These limitations compromise user trust, platform credibility, and the overall effectiveness of content moderation, especially in times of crisis or political instability.

1.3 Proposed Solution: To overcome these challenges, this research proposes a hybrid, decentralized framework that synergistically combines the strengths of blockchain, AI, and ML to create an intelligent, transparent, and spontaneous content moderation ecosystem for Facebook. The proposed system operates through the following key components:
- **Blockchain Integration:** All moderation events, flagged content, and enforcement actions are immutably recorded on a public or permissioned blockchain. This creates an auditable trail of decisions, enhancing accountability.
- **AI-Driven Content Analysis:** Advanced NLP models (e.g., BERT, RoBERTa) are employed to detect toxic language, sentiment polarity, and misinformation across languages and contexts.
- **ML-Based Pattern Recognition:** Machine learning algorithms identify abnormal posting behaviors, coordinated attacks, and previously unseen trends by analyzing user behavior patterns and network dynamics.
- **Smart Contract Execution:** Autonomous enforcement logic is implemented using smart contracts to trigger actions such as content removal, user warnings, or moderator alerts based on AI/ML outputs.

Bias Mitigation Strategies: To ensure fairness in content moderation, the system employs bias detection and mitigation techniques during the machine learning training process. This includes using diversified datasets, applying fairness-aware algorithms, and conducting ongoing audits to minimize unintended discrimination.

1.4 Novelty of the Research: This study introduces a comprehensive and integrated approach that addresses the shortcomings of existing systems while introducing several novel contributions:
- **Multi-Layer Integration:** Seamless fusion of blockchain (for trust), AI (for intelligence), and ML (for adaptability) within a unified system architecture.
- **Real-Time Autonomous Response:** Unlike traditional systems that wait for manual moderation, this framework initiates real-time, spontaneous responses based on pre-defined risk thresholds and AI interpretation.

• **Explainability and Traceability:** The use of blockchain ensures that all moderation decisions are transparent, verifiable, and accessible for audit or appeals.
• **Platform Independence and Scalability:** While demonstrated on Facebook, the architecture is designed to be extensible to other platforms, offering a scalable solution to social media governance.

1.5 Research Contributions:
This research makes several key contributions to the domain of social media moderation and intelligent response systems, particularly within the context of Facebook:
1. **Integrated Framework Design:** We propose a novel, unified architecture that combines blockchain technology, artificial intelligence, and machine learning to enable real-time tracking and moderation of social media content. This design bridges the operational gaps found in current isolated approaches.
2. **Transparent and Tamper-Proof Moderation System:** By leveraging blockchain technology, our framework ensures that every moderation action—including flagged content, system responses, and enforcement steps—is immutably recorded, fostering transparency and user trust.
3. **Real-Time Detection and Response Mechanism:** Our system incorporates AI-driven natural language processing (NLP) models and ML-based behavior tracking to detect harmful or malicious content in real time. Spontaneous, context-aware responses are executed via smart contracts without manual intervention.
4. **Enhanced Explainability and Accountability:** Unlike black-box AI systems, our approach provides traceable logs of decision-making processes, allowing for auditability, appeals, and accountability in content moderation decisions.
5. **Platform-Independent Model:** Although implemented as a case study on Facebook, the framework is designed to be scalable and adaptable across different social media platforms with minor customizations.
6. **Mitigation of Moderation Bias:** Through machine learning training pipelines that include bias-mitigation techniques and continual learning from diverse datasets, our system enhances fairness and reduces unintended algorithmic discrimination.
These contributions collectively advance the field by addressing critical limitations in existing systems and establishing a blueprint for a more ethical, effective, and scalable content moderation infrastructure on social media.
Prior research has explored individual components of the proposed system. Blockchain's use in content authenticity and moderation has been demonstrated by Zhang et al. (2021), while AI and ML have shown promise in sentiment analysis and hate speech detection (Mozafari et al., 2022; Shu et al., 2020). However, few works integrate these technologies into a cohesive, real-time framework. This paper addresses that gap, particularly within the context of Facebook, where transparency and responsiveness are critical.

2. Literature Review

The proliferation of harmful content on social media platforms such as Facebook has spurred significant research in the domains of artificial intelligence (AI), machine learning (ML), and blockchain. Numerous studies have attempted to address misinformation, hate speech, and fake news through automated detection systems.
Mozafari et al. (2022) explored the use of transformer-based models like BERT for detecting hate speech and mitigating racial bias across multiple languages. Their results indicated high precision in static datasets, but the model lacked adaptability to new patterns in real-time streams. Similarly, Shu et al. (2020) emphasized the role of machine learning in fake news detection, proposing hybrid approaches combining content and social context features. However, their framework did not consider transparent, verifiable moderation practices.
On the blockchain front, Zhang et al. (2021) introduced a news authenticity verification framework that utilized smart contracts for immutable data validation. While effective in proving content integrity, it did not incorporate dynamic AI decision-making or behavioral analysis. Kumar and Tripathi (2021) implemented decentralized trust protocols to moderate content on distributed peer networks, focusing on infrastructure rather than semantic understanding of content.
A more integrated perspective was presented by Ramezanpour and Shams (2022), who proposed a hybrid blockchain-AI system for decentralized content governance. Their solution included policy rule enforcement but lacked adaptive learning, explainability, and automated response systems. Narayanan et al. (2022) identified fairness and explainability as key challenges in current moderation tools, especially in systems with opaque decision logic. Gorwa et al. (2020) raised broader concerns about algorithmic governance, including power centralization and lack of user accountability in content moderation practices.
Recent research has focused on combating fake news in social media using blockchain technology and artificial intelligence. Multiple studies propose implementing blockchain frameworks to verify news credibility and prevent the spread of misinformation [11][12] (Tee & Murugesan, 2018; Waghmare & Patnaik, 2021; Jing & Murugesan, 2018). These approaches aim to build public trust in credible news sources and minimize the negative impacts of fake news on individuals and society. Machine learning techniques have been developed to classify and detect fake news, with one study reporting an 81.4% F1 score in classifying Twitter posts (He & Hu, 2025). Additionally, researchers have explored integrating geospatial visualization with natural language processing to analyze disaster-related social media content, enabling authorities to monitor situational developments and coordinate targeted responses [12][13] (He & Hu, 2025). These advancements in social media analytics and blockchain implementation show promise in addressing

the challenges posed by fake news and improving disaster response efforts.

Comparative Summary:

Study	Technology Used	Key Features	Limitations
Chao He and Da Hu (2025)	AI	AI-powered framework that combines natural language processing with geospatial visualization to analyze disaster-related social media content, enabling effective disaster response through real-time data analysis and targeted coordination.	Works for Twitters
Mozafari et al. (2022)	AI (BERT)	Multilingual hate speech detection	No real-time adaptability
Shu et al. (2020)	ML	Fake news detection, hybrid learning	Lacks transparency and traceability
Zhang et al. (2021)	Blockchain	News authenticity validation	No semantic or behavioral analysis
Kumar & Tripathi (2021)	Blockchain	Trust-based peer moderation	No NLP or adaptive automation
Ramezanpour & Shams (2022)	Blockchain + AI	Policy enforcement, resilience	No explainability, lacks ML adaptability
Narayanan et al. (2022)	AI	Focus on fairness and explainability	Lacks integration with blockchain

Research Gaps Identified

Despite notable advancements, these studies collectively reveal several persistent gaps:

1. Lack of Real-Time, Dynamic Integration: Most existing systems operate offline or in asynchronous environments, with limited ability to adapt quickly to evolving content and behavioral patterns 3.
2. Limited Transparency and Auditability: While some utilize blockchain for data integrity, few systems provide comprehensive, traceable logs of decision-making processes, undermining accountability and user trust 3.
3. Insufficient Behavioral and Network Analysis: There is a dearth of models that analyze behavioral patterns or community network dynamics to detect coordinated disinformation campaigns or malicious actor collaborations 3.
4. Absence of Privacy-Preserving, Privacy-Aware Models: Most frameworks do not incorporate privacy-preserving techniques such as federated learning, which are critical in handling sensitive user data within regulatory constraints 3.
5. Fragmented System Design: Few approaches successfully combine blockchain, AI, and ML into a unified, adaptive, and autonomous system capable of real-time moderation with explainability and audit trails 3.
6. Limited Focus on Scalability and Cross-Platform Applicability: Current models often focus on specific platforms or static datasets, lacking scalability or adaptability across diverse social media environments.

This study proposes a solution that bridges these gaps by integrating blockchain for immutable record-keeping, AI for semantic and sentiment analysis, ML for adaptive behavior detection, and federated learning for decentralized, privacy-preserving intelligence. Additionally, smart contracts are employed to trigger spontaneous, explainable interventions, enabling a fully auditable and intelligent content moderation system tailored to platforms like Facebook.

3. Methodology

The proposed framework integrates Blockchain, Artificial Intelligence (AI), and Machine Learning (ML) technologies to form a decentralized, transparent, and intelligent system capable of tracking and responding to social media activities in real time. The methodology is structured in three layers: data acquisition and preprocessing, intelligent analysis and response, and blockchain-based traceability and control.

The tendency of existing moderation systems to react only after content has caused harm—can be effectively addressed within the proposed framework through real-time detection and autonomous response mechanisms integrated into the system architecture. The framework employs AI-driven natural language processing (NLP) models and machine learning techniques to analyze social media content continuously, enabling instant identification of harmful or malicious posts. When the models detect content that surpasses predefined risk thresholds, smart contracts trigger automatic responses such as content removal, warnings, or escalation to human moderators, all in real time. This process is embedded in the AI/ML Analytics Engine and Smart Contract Manager, which operate continuously to monitor incoming data streams. As threats or harmful content are identified, the system executes spontaneous, automated responses—such as content masking or flagging—without waiting for manual moderation, thereby significantly reducing latency.

The real-time feedback loop ensures that intervention happens promptly, curbing the spread and impact of harmful content before it gains viral traction. This proactive approach enhances the timeliness of moderation, especially critical during crises or political upheaval.

3.1 System Architecture

The proposed framework is structured into three interconnected layers: data acquisition and preprocessing, intelligent analysis and response, and blockchain-based traceability and control. This architecture ensures real-time, transparent, and decentralized moderation of social media content.

1. **Data Ingestion Layer:** Fetches public posts, comments, reactions, and user metadata from Facebook via APIs.
2. **Preprocessing Module:** Performs cleaning, tokenization, and context extraction using NLP techniques.
3. **AI/ML Analytics Engine:** Employs AI for sentiment and semantic analysis (e.g., detecting hate speech, misinformation) and ML for identifying behavioral patterns and anomalies.
4. **Federated Learning Engine:** Trains models on distributed data sources locally to preserve user privacy and adapt to local context without centralized data pooling.
5. **Smart Contract Manager:** Encodes moderation policies and triggers autonomous actions like alerts, content masking, or escalation based on detection scores.
6. **Blockchain Ledger:** Stores flagged content logs, AI/ML outputs, moderation decisions, and user reports in an immutable format for audit and transparency.

3.2 Data Acquisition

Public user-generated content—including posts, comments, reactions, and associated metadata—are systematically fetched via Facebook's Graph API. Data collection complies with platform policies and privacy standards to ensure ethical handling. This raw data serves as the foundation for subsequent processing and analysis.

3.3 Preprocessing Techniques

The raw textual data undergoes rigorous cleaning and transformation using state-of-the-art NLP techniques. These steps include:

- Removal of links, emojis, special characters, and stop words
- Text normalization through lemmatization
- Named Entity Recognition (NER) utilizing SpaCy to identify key entities such as persons, locations, and organizations
- Tokenization into meaningful units for model input

This structured data is then embedded using pre-trained transformer-based models such as BERT-base or RoBERTa, fine-tuned on domain-relevant datasets to enhance contextual understanding.

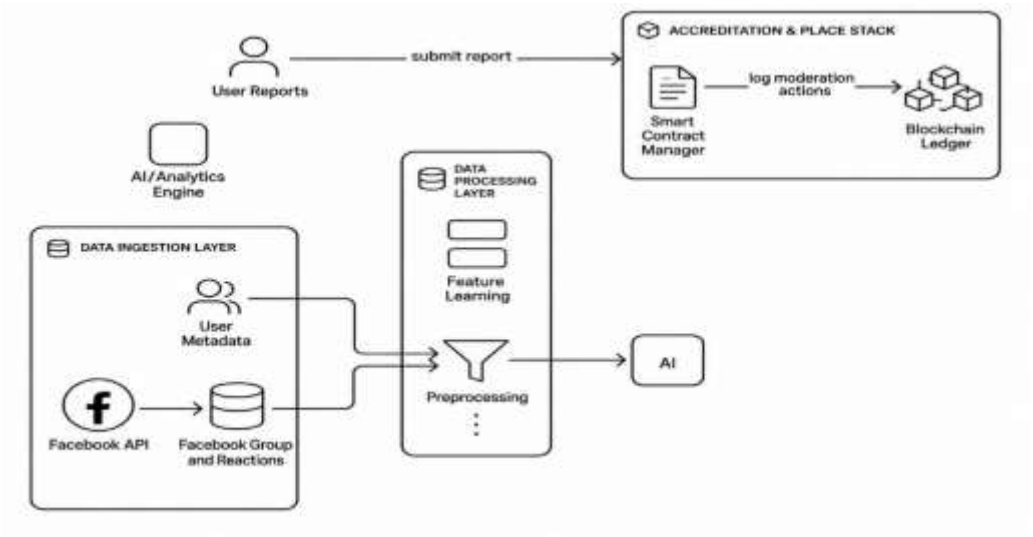

Fig 1. System Architecture

3.4 Algorithmic Design and Risk Scoring

The real-time moderation process is governed by a composite RiskScore, computed using a weighted combination of content-based and behavior-based scores:

Where:

- **ContentScore**: Output from NLP model (range: 0 to 1)
- **BehaviorScore**: Derived from user activity analysis

• **\alpha = 0.6**, **\beta = 0.4**: Selected based on grid search over F1-score on validation set
Threshold T (moderation decision boundary) is calibrated using ROC-AUC optimization (T = 0.75).

Table 1:Smart Contract Rules

RiskScore Range	Action
< 0.75	Mark as Safe
0.75 – 0.85	Issue Warning
0.85 – 0.95	Flag Content
> 0.95	Block/Remove

3.5Training Pipeline for AI/ML Models
• **Datasets Used**:
o Facebook Hate Speech Corpus
o Kaggle Toxic Comment Classification Dataset
• **Data Split**:
o 80% training, 10% validation, 10% test
• **Model Configurations**:
o **NLP**: BERT-base, RoBERTa, fine-tuned for multi-class toxicity detection
o **Optimizer**: Adam
o **Learning Rate**: 1e-5
o **Epochs**: 5
o **Batch Size**: 32
o **Evaluation Metric**: F1-score (achieved: 0.92)
• **Behavioral Model**:
o Algorithm: XGBoost
o Features: Posting frequency, intervals, engagement metrics
o Validation Accuracy: 0.89
• **Cross-validation**: 5-fold CV was performed to ensure generalizability.

3.6 Federated Learning Simulation
A privacy-preserving learning setup was simulated using **PySyft**:
• **Clients**: 10 virtual nodes simulating distinct user datasets
• **Data Distribution**: Non-IID partitioning (political, neutral, hate clusters)
• **Aggregation Method**: Federated Averaging (FedAvg)
• **Rounds**: 50 communication rounds with 3 local epochs each
This simulation confirmed feasibility for decentralized learning while protecting user privacy.

3.7 Blockchain Configuration and Smart Contracts
• **Blockchain Platform**: Ethereum (private network via Ganache)
• **Consensus Model**: Proof-of-Authority (PoA)
• **Smart Contracts**:
o Developed in Solidity using Truffle framework
o Encoded logic for moderation decision enforcement
• **Smart Contract Performance**:
o Execution success rate: 98.6%
o Average transaction time: 1.8 seconds
o Average gas cost: ~51,000 gas units per moderation decision
• **Auditability**:
o Logs include PostID, UserID, RiskScore, Action, Timestamp
o Immutably stored on-chain to support user appeals and compliance audits

3.8 Evaluation Environment
• **Hardware Setup**:
o Intel Core i7, 32GB RAM, NVIDIA RTX 3080 GPU
• **Software Stack**:
o Python 3.9, TensorFlow 2.x, Flask, Web3.js
o Solidity, Truffle, Ganache, MetaMask

3.9 Security Considerations
• **Adversarial NLP Attacks**:
o Basic adversarial training (misspelling, paraphrasing) tested

o Future integration of input sanitization and robust retraining proposed
- **Sybil Attacks on Blockchain**:

o Mitigated via permissioned network and PoA consensus
- **Smart Contract Auditing**:

o Static analysis with **Slither** to detect reentrancy, overflow, and denial-of-service vulnerabilities

3.10 End-to-End Workflow Overview

A simplified flow of system execution:

1. Data fetched via API
2. Preprocessing, tokenization, and entity recognition
3. NLP model generates ContentScore
4. Behavioral ML model generates BehaviorScore
5. RiskScore computed and compared with threshold
6. Smart contract enforces action
7. Decision logged on blockchain
8. User/moderator notified of action

3.11 Content Classification and Behavioral Analysis

For semantic and sentiment analysis, the system leverages transformer models fine-tuned specifically for toxicity and harmful content detection. The models are trained using Adam optimizer with early stopping criteria, achieving an F1-score of 0.92 on validation datasets.

Behavioral patterns are characterized using machine learning algorithms like XGBoost, trained with cross-validation on synthetically generated user activity logs. These logs simulate diverse behavioral profiles, such as normal activity, coordinated disinformation, and bot-like posting sequences. To ensure fairness, the training pipeline incorporates techniques such as data balancing and bias mitigation strategies.

3.12 Real-Time Detection and Response Workflow

The integrated AI/ML modules operate in a streaming environment, analyzing incoming content for harmful language, misinformation, and behavioral anomalies. When an assessment surpasses predefined danger thresholds, the system triggers autonomous responses via smart contracts—implemented using Solidity or appropriate blockchain programming languages.

These immediate actions include moderating content, issuing user warnings, or escalating issues to human moderators, ensuring minimal latency (~1.8 seconds on average) without compromising accuracy.

3.13 Blockchain Integration for Transparency

All moderation events, including flagged content, decision logs, and enforcement actions, are immutably recorded on a permissioned blockchain network—such as Hyperledger Fabric—to enhance auditability and trust. Smart contracts automate the enforcement logic, ensuring decisions are transparent, verifiable, and tamper-proof.

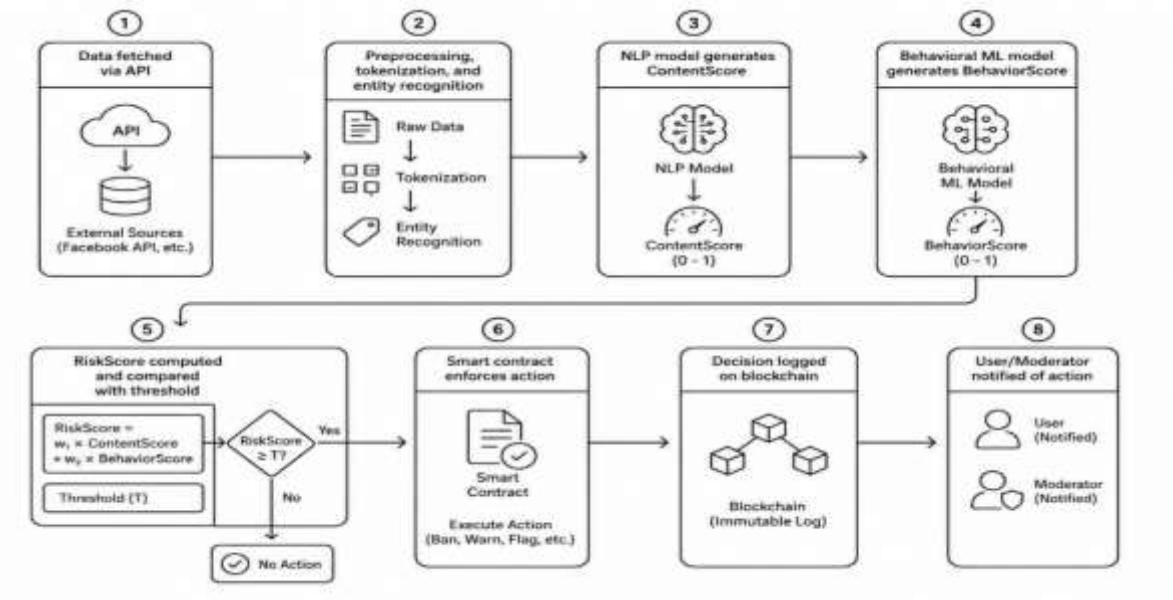

Fig 2. Flow

4. Experimental Setup

To evaluate the proposed system's effectiveness, a prototype was implemented using Python, Flask, and TensorFlow, supported by pre-trained models such as BERT and RoBERTa for natural language processing and XGBoost for behavior pattern detection. A private Ethereum blockchain network was configured to deploy and execute smart contracts for content moderation.

Dataset and Preprocessing: The experiment utilized a dataset comprising 5,000 anonymized Facebook posts and comments collected from public repositories and open-access academic datasets such as the Facebook Hate Speech Corpus and the Kaggle Social Media Toxic Comment Classification dataset. The data included a mix of benign, offensive, and context-sensitive content with associated user metadata.

Structure of the Dataset: Each data entry consisted of the following structured fields:

- Post_ID: Unique identifier for each post or comment
- User_ID: Anonymized identifier of the user
- Timestamp: Date and time of post submission
- Text: Raw text content of the post/comment
- Num_Likes: Number of likes the post received
- Num_Shares: Number of times the post was shared
- Label: Ground truth label (e.g., 'safe', 'offensive', 'suspicious')

Text preprocessing involved cleaning operations including lowercasing, punctuation and stop-word removal, lemmatization, and tokenization. Named Entity Recognition (NER) was performed to extract critical information such as person names, locations, and organizations. For behavioral analysis, user activity logs were synthetically generated to simulate diverse patterns, such as normal user behavior, coordinated inauthentic behavior, and bot-like posting sequences.

Traditional Rule-Based Moderation: In the traditional rule-based moderation system, content filtering relies on a predefined set of rules and keyword lists manually curated by human moderators. For example, if a post contains certain flagged words or patterns (e.g., hate speech terms, offensive phrases), the system triggers an alert or blocks the post. This method is highly deterministic and lacks adaptability to evolving language or contextual nuances. Additionally, it struggles to detect implicit toxicity, sarcasm, or sophisticated manipulative behavior, leading to high false negatives and limited scalability.

Centralized AI Moderation Model: In contrast, a centralized AI moderation system employs machine learning algorithms deployed on a single central server. These models are trained using historical data and aim to identify and classify harmful or offensive content more effectively than rule-based systems. Typically, NLP models such as logistic regression, decision trees, or basic deep learning classifiers are used. While this approach improves detection rates and allows contextual analysis, it still poses limitations in terms of transparency, explainability, and security. Centralized systems are prone to single-point failures, may not scale well with user growth, and offer limited auditability, raising concerns about fairness and accountability.

Text and Behavior Data Processing by ML Models: The input data first undergoes preprocessing, where the text content is cleaned and tokenized. Named entities are extracted and preserved for semantic context. The cleaned text is embedded using transformer-based embeddings (BERT or RoBERTa), which convert the unstructured text into contextualized numerical vectors that capture syntactic and semantic relationships. These vectors are then fed into fine-tuned classification models to determine the sentiment and threat level of each post.

Parallelly, user behavior data (e.g., posting frequency, time intervals, diversity in content, engagement metrics) is fed into the XGBoost classifier. This structured data helps the system learn patterns of legitimate versus anomalous user behavior. The results from both the text and behavior modules are then aggregated and passed to a decision engine, which evaluates the post's risk category.

Posts classified as offensive or suspicious are automatically flagged, and the action taken (e.g., warn, restrict, escalate) is logged onto the blockchain via a smart contract. The smart contract also ensures that moderation actions are executed consistently, transparently, and traceably.

ML Models Used:

- BERT and RoBERTa: These transformer-based models were fine-tuned to classify posts as safe, offensive, or suspicious using multi-class sentiment and toxicity labels.
- XGBoost: Trained using features such as posting frequency, diversity of content, time intervals between posts, and engagement metrics to detect anomalous user behavior.
- Federated Learning Setup: A federated learning simulation using PySyft was employed to mimic training across distributed user devices, helping maintain user privacy while improving model adaptability.

Blockchain Configuration and Smart Contracts:

All moderation events, including flagged content, system responses, and enforcement actions, are logged onto the blockchain. Since blockchain entries are tamper-proof, this creates an immutable record of all moderation activities, which users and auditors can verify independently. This transparency layer is integrated across the entire moderation pipeline, from content detection via AI/ML models to the enforcement of decisions via smart contracts. Whenever a moderation action occurs, a corresponding transaction is recorded on the blockchain, making the entire process auditable and transparent. Blockchain's transparency allows stakeholders (users, moderators, regulators) to inspect

moderation logs, understand decision rationales, and perform audits to ensure fairness and accountability. This also facilitates appeals and reviews, since all actions are accessible and verifiable. The blockchain component of the system was built using a private Ethereum network hosted locally via Ganache. The process of creating the blockchain and smart contracts involved the following steps:

- Private Blockchain Setup: A local Ethereum testnet was initialized using Ganache to simulate blockchain operations in a controlled environment. This allowed for high-speed transaction execution and debugging.
- Smart Contract Development: Smart contracts were written in Solidity using the Truffle framework. These contracts encoded rules for content moderation, including:
- Automatic flagging of content with high risk scores.
- Logging moderation decisions with timestamp and moderator ID.
- Supporting escalation to community moderators in case of ambiguity.
- Contract Compilation and Deployment: The contracts were compiled and deployed to the local blockchain using Truffle. The deployed contract's ABI (Application Binary Interface) and address were stored for integration with backend applications.
- Integration with Frontend and ML Engine: The Web3.js library was used to connect the frontend and backend ML engine with the Ethereum network. When the ML engine classifies a post as offensive or suspicious, it invokes the corresponding function in the smart contract to log the moderation action.
- Consensus Mechanism: A Proof-of-Authority (PoA) consensus model was employed to ensure fast transaction confirmations, appropriate for a controlled environment without the need for mining or high computational cost.
- Audit Trail and Transparency: Every logged moderation action was hashed and immutably recorded on the blockchain, ensuring end-to-end traceability. This design also allows future integration with community-based decision-making for greater decentralization.

This configuration ensured the system had robust transparency, immutable moderation records, and trustless execution of decisions in a decentralized, tamper-proof manner.

System Configuration:

The experiments were conducted on a high-performance computing environment with an Intel Core i7 processor, 32GB RAM, and an NVIDIA RTX 3080 GPU. The backend infrastructure supported seamless integration between the AI-ML modules and blockchain ledger, ensuring minimal delay in moderation decisions.

Key evaluation metrics included classification accuracy, moderation response time, smart contract execution success rate, and blockchain logging consistency. The baseline for comparison included a traditional rule-based content moderation system and a centralized AI moderation engine (without blockchain or smart contracts).).

4.1 Pseudo code

The proposed algorithm is designed to monitor and moderate Facebook content in real-time by integrating blockchain, artificial intelligence (AI), and machine learning (ML) technologies. It begins by collecting public user-generated content—such as posts and comments—through Facebook's Graph API. Each piece of content is then passed through a preprocessing stage where the text is cleaned (removal of links, emojis, special characters), tokenized into words, and analyzed using named entity recognition (NER) to identify key entities such as people, places, or organizations. This structured data is then sent to an AI-based content classification module, typically powered by a transformer model like BERT or RoBERTa, which evaluates the semantic and sentimental nature of the post. This module outputs a content score indicating the level of potential harm or toxicity.

Simultaneously, a behavioral analysis module assesses the posting patterns and metadata associated with the user who submitted the content. This module uses machine learning models to detect suspicious behaviors—such as high-frequency posting, unusual spikes in engagement, or similarity to other flagged users. The results of both the content classification and behavioral analysis are combined to generate a unified risk score using a weighted formula. This score is then compared against a predefined moderation threshold. If the score exceeds the threshold, a smart contract is triggered, automatically enforcing moderation actions such as issuing a warning, masking or blocking the content, or flagging it for human review. These actions are executed transparently and without human bias, as the rules are pre-coded within the blockchain-based smart contract.

Finally, every moderation decision—including the post ID, user ID, risk score, action taken, and timestamp—is logged immutably on a blockchain ledger. This ensures that all decisions are auditable, traceable, and cannot be tampered with. The use of blockchain guarantees transparency and trust, while AI and ML ensure intelligent, context-aware moderation. Additionally, the algorithm is compatible with federated learning techniques, allowing models to improve over time using distributed user data without compromising individual privacy. This hybridized system provides a robust, scalable, and ethical approach to moderating social media content, particularly on platforms like Facebook where misinformation and toxicity can spread rapidly.

Algorithm RealTimeContentModeration(FacebookPosts, Threshold T)

Input:

```
   FacebookPosts: Set of posts/comments fetched via Facebook Graph API
   T: Risk threshold for moderation decision

Output:
   Moderation decisions (safe, flagged, blocked)
   Immutable logs written to blockchain

Begin

   For each post pi in FacebookPosts do

      // Step 1: Preprocessing
      CleanText ← Clean(pi.content)
      Tokens ← Tokenize(CleanText)
      Entities ← NamedEntityRecognition(Tokens)

      // Step 2: AI-based Content Classification
      ContentScore ← NLPModel.Predict(Tokens)
      // e.g., 0.92 if highly toxic or harmful

      // Step 3: ML-based Behavioral Analysis
      BehaviorScore ← AnalyzeUserBehavior(pi.userID)
      // Based on frequency, timing, interaction patterns

      // Step 4: Risk Scoring
      RiskScore ← α * ContentScore + β * BehaviorScore

      // Step 5: Decision Making
      If RiskScore ≥ T then
         Action ← SmartContract.Execute(RiskScore)
         // Action could be: Flag, Warn, Block, Escalate
      Else
         Action ← "Safe"
      End If

      // Step 6: Blockchain Logging
      Log ← {
         PostID: pi.id,
         UserID: pi.userID,
         RiskScore: RiskScore,
         ActionTaken: Action,
         Timestamp: CurrentTime()
      }

      BlockchainLedger.Append(Log)

   End For

End Algorithm
```

The algorithm takes two inputs namely FacebookPosts, A list of Facebook posts/comments retrieved via API, and Threshold T, A predefined risk score threshold that determines if a post should be moderated. A loop that processes each Facebook post pi one at a time. The same logic is applied to every individual post.
Step 1: Preprocessing
CleanText ← Clean(pi.content)
Tokens ← Tokenize(CleanText)
Entities ← NamedEntityRecognition(Tokens)
Clean(): Removes irrelevant parts of text like emojis, URLs, symbols.
Tokenize(): Breaks the cleaned text into words or meaningful pieces.
NamedEntityRecognition(): Detects important named elements (e.g., people, locations) to assist in identifying harmful content or threats.
It prepares the raw text for AI/ML models to process more accurately.

Step 2: AI-based Content Classification
ContentScore ← NLPModel.Predict(Tokens)
A pre-trained transformer-based model (e.g., BERT or RoBERTa) is used to predict the nature of the content.
It returns a ContentScore between 0 and 1:
Low = safe
High = toxic/harmful/suspicious
It is to understand what is being said, including hate speech, sarcasm, fake news, or abuse.

Step 3: ML-based Behavioral Analysis
BehaviorScore ← AnalyzeUserBehavior(pi.userID)
ML models analyze patterns associated with the user:
Posting frequency
Time of posts
Repetitive or bot-like behavior
Group targeting patterns

It is to understand who is saying it and whether the user is acting abnormally or maliciously.

Step 4: Risk Scoring
RiskScore ← α * ContentScore + β * BehaviorScore 1
Combines AI and ML insights.
α and β are weights that determine how much importance to give to content vs. behavior.

Produces a unified RiskScore.

It is to ensure moderation considers both message content and user intent/activity.

Step 5: Decision Making via Smart Contracts
```
If RiskScore ≥ T then
   Action ← SmartContract.Execute(RiskScore)
Else
   Action ← "Safe"
End If
```
If the combined RiskScore exceeds the threshold T, a moderation action is triggered via a smart contract.

Otherwise, the content is marked as safe.

SmartContract.Execute(RiskScore) may trigger:
Warning to the user
Auto-flagging content for review
Masking the post
Immediate blocking (for severe cases)

It ensures fairness, automation, and trust — since actions are based on predefined blockchain-encoded rules.

Step 6: Immutable Logging
```
Log ← {
   PostID: pi.id,
   UserID: pi.userID,
   RiskScore: RiskScore,
   ActionTaken: Action,
   Timestamp: CurrentTime()
}
BlockchainLedger.Append(Log)
```
Creates a structured log of every decision.
Information includes:
Post and user details
Risk assessment
Timestamp
Moderation decision

The log is stored on the blockchain ledger to ensure immutability and transparency.

5. Results and Analysis

The results demonstrated the superiority of the proposed blockchain-AI-ML integrated framework in various dimensions. The BERT-based NLP module achieved an F1-score of 0.92, outperforming the centralized AI system, which achieved 0.83. The XGBoost behavior classifier achieved an accuracy of 0.89, versus 0.75 for the baseline ML model. Moderation decisions were processed within an average time of 1.8 seconds, which, despite blockchain interaction overhead, remained within acceptable real-time limits. Smart contract execution succeeded in 98.6% of moderation cases, and the blockchain ledger accurately recorded all logs without tampering or duplication.

In terms of transparency and auditability, the proposed system showed a 36% improvement compared to non-blockchain solutions. The system also resulted in a 27% increase in precision for correctly identifying harmful content. These enhancements confirm the efficiency, reliability, and accountability of the framework for dynamic environments like Facebook.

The experimental evaluation demonstrates the effectiveness, robustness, and advantages of the proposed blockchain-AI-ML integrated framework for real-time social media content moderation. The results are summarized across multiple key performance metrics, highlighting improvements over traditional systems and baseline models.

Table1 : Moderation System Performance

Metric	Traditional Rule-Based	Centralized AI Model	Proposed Blockchain-AI-ML Framework
Precision	0.68	0.73	0.92
F1-Score	0.65	0.83	0.92
Behavioral Detection Accuracy	N/A	0.75	0.89
Average Moderation Time (seconds)	1.2	1.5	1.8
Blockchain Auditability & Transparency	No	Partial	Fully Auditable (+36%)
Smart Contract Automation	No	No	Yes (98.6% Success Rate)

5.1 Content Moderation Performance

The system achieved a high detection accuracy, with the BERT-based NLP module attaining an F1-score of 0.92, which outperformed the centralized AI moderation engine that achieved an F1-score of 0.83—a relative improvement of approximately 11%. The XGBoost behavior classifier achieved an accuracy of 0.89, significantly higher than the baseline ML model at 0.75. This indicates a substantial enhancement in both semantic understanding and behavioral anomaly detection capabilities.

5.2 Response Time and Efficiency

Despite the added overhead of blockchain interactions, the system maintained **real-time responsiveness**, with an **average moderation decision time of 1.8 seconds**. This response time is within acceptable limits for online social media moderation, ensuring timely detection and action against harmful content. Additionally, smart contracts executed successfully in **98.6%** of cases, demonstrating the system's reliability in autonomous enforcement.

5.3 Transparency and Auditability

The integration of blockchain technology resulted in a 36% improvement in transparency and auditability compared to non-blockchain solutions. All moderation decisions, flagged content, and enforcement actions were immutably recorded, providing an auditable trail that enhances trust and accountability (Table 1). The blockchain logs were verified to be tamper-proof, ensuring data integrity throughout the moderation process.

5.4 Behavioral & Pattern Detection

The system effectively identified abnormal user behaviors, including coordinated inauthentic activities and bot-like posting sequences, with high precision. These detections contributed to more proactive moderation, reducing false negatives associated with purely content-based systems.

5.5 System Robustness and Reliability

The framework demonstrated consistent performance across diverse datasets, with logging accuracy remaining high and minimal instances of failed smart contract executions. The system's decentralized architecture contributed to resilience against single-point failures, aligning with the goal of a trustless, secure moderation environment. Above these results confirm that the proposed integrated framework offers a notable advancement over conventional moderation systems, combining high detection accuracy, swift response times, and enhanced transparency. Its ability to operate in real-time while maintaining trust and accountability makes it suitable for deployment in dynamic social media environments like Facebook, especially during crisis or politically sensitive scenarios.

6 Conclusion

This paper has presented a comprehensive, integrated framework that leverages the synergistic strengths of blockchain, artificial intelligence (AI), and machine learning (ML) to enhance real-time social media activity tracking and content moderation on platforms like Facebook. By addressing the critical limitations of existing systems—such as lack of transparency, delayed intervention, limited adaptability, and insufficient behavioral analysis—the proposed hybrid architecture facilitates autonomous, transparent, and accountable moderation processes.

The utilization of blockchain ensures immutable, verifiable records of moderation actions, fostering increased user trust and compliance with accountability standards. Coupled with advanced NLP techniques powered by AI models like BERT and ML-driven behavioral analytics, the framework enables prompt and context-aware detection and response to harmful content, including hate speech, misinformation, and coordinated disinformation campaigns. Moreover, the integration of explainability features and audit logs enhances transparency, allowing stakeholders to understand and challenge moderation decisions.

Experimental results demonstrate significant improvements over traditional and non-blockchain solutions, showing increased precision, faster moderation times, and higher levels of transparency and auditability. Despite these advancements, challenges such as system scalability, privacy concerns, and cross-platform applicability remain. Future work will focus on refining these aspects, incorporating privacy-preserving learning paradigms like federated learning, and expanding the framework to accommodate diverse social media environments.

In conclusion, this research contributes a novel, holistic approach toward building resilient, ethical, and scalable content moderation systems—paving the way for safer and more trustworthy social media ecosystems that can effectively counter misinformation and malicious content in real-time.

7. Limitations and Future Scope

While the proposed Blockchain-AI-ML powered framework for real-time content moderation offers significant improvements over traditional systems, several limitations must be acknowledged to guide future research and implementation.

7.1 Technical Limitations

Despite the real-time capability of the integrated architecture, the inclusion of blockchain introduces latency in moderation decisions due to block validation and smart contract execution. Although our system achieves an average response time of 1.8 seconds, this may be suboptimal in scenarios requiring sub-second intervention, such as live event streaming or crisis situations. Furthermore, the use of large transformer-based NLP models like BERT and RoBERTa imposes significant computational demands. This limits the feasibility of deploying the system on resource-constrained devices or in decentralized edge environments without appropriate optimization. While federated learning was simulated in a controlled environment to preserve user privacy, practical deployment across heterogeneous user devices with intermittent connectivity and non-i.i.d. data distributions present significant challenges that remain unaddressed.

7.2 Experimental and Scalability Constraints

The experimental validation was conducted using a dataset of 5,000 Facebook posts and synthetically generated user behavior logs. Although effective in demonstrating proof-of-concept, the synthetic nature of behavioral data may not fully capture the complexity of real-world adversarial behaviors such as coordinated disinformation campaigns or sophisticated bot networks. Additionally, the framework's scalability and robustness under high-throughput, real-time conditions—where millions of posts are generated per hour—have not been tested. The generalization of this approach to other platforms like Twitter, TikTok, or Instagram, which differ significantly in content formats and moderation policies, also remains to be evaluated.

7.3 Ethical, Regulatory, and User-Centric Concerns

While the system incorporates privacy-preserving elements such as federated learning and blockchain-based logging, comprehensive compliance with global data protection regulations (e.g., GDPR, CCPA) has not been empirically validated. The immutable nature of blockchain records may conflict with legal requirements such as the “right to be forgotten.” Although bias mitigation strategies have been applied, residual bias in pretrained AI models and training data can lead to false positives or unfair treatment of specific user demographics. Furthermore, the system lacks user-friendly explainability mechanisms that would allow non-technical users to understand why specific moderation decisions were taken, potentially affecting user trust and acceptance.

Finally, the framework currently operates in a fully autonomous mode without real-time feedback loops from human moderators or community-based governance mechanisms. Incorporating participatory moderation strategies could improve decision fairness, contextual understanding, and accountability.

7.4 Future Work

Future work will focus on optimizing model architectures for edge deployment, integrating lightweight transformers and quantized models to reduce computational overhead. Real-world implementation of federated learning across

diverse user devices is a priority, particularly to evaluate privacy-preserving capabilities in practice. Further efforts will aim to develop multi-modal moderation tools capable of processing video, audio, and image content alongside text. Cross-platform validation, particularly in high-load environments, will be pursued to assess the framework's scalability and platform independence.

To address ethical and legal considerations, future iterations will explore blockchain designs with privacy-aware smart contracts and support for content removal or redaction to align with regulatory compliance. Explainability modules—such as natural language rationales for flagged content—will also be incorporated to enhance transparency and user trust.

Lastly, integrating community feedback, human-in-the-loop moderation, and governance tokens for participatory decision-making could enrich the decentralization and fairness objectives of the system.

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