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Revolutionizing Healthcare Fundraising: Medical Crowdfunding Enhanced by Blockchain and Machine Learning

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Abstract

Medical crowdfunding has increasingly become a crucial method for individuals to gather funds during medical crises. Nevertheless, conventional crowdfunding platforms face challenges such as fraudulent initiatives, unclear fund distribution, and ineffective targeting. This study introduces a comprehensive framework that utilizes blockchain technology and Machine Learning (ML) to improve transparency, security, and efficiency in medical crowdfunding. Blockchain technology is used to establish an unchangeable and decentralized record of transactions while facilitating automated fund management through smart contracts. At the same time, ML algorithms evaluate campaign data to identify fraud, verify legitimacy, and forecast campaign success. Our proposed system is assessed against current solutions and shows notable enhancements in reliability and performance. The paper includes comparative analysis, architectural diagrams, and performance assessment utilizing both real and synthetic datasets, effectively advocating for the implementation of intelligent, decentralized medical crowdfunding systems.

Keywords: *Medical crowdfunding, Healthcare fundraising, Blockchain, Machine learning*

1. Introduction

In recent years, medical crowdfunding has seen substantial growth, providing essential support to those requiring immediate healthcare funding. With the rise of digital platforms such as GoFundMe, Milaap, Ketto, and ImpactGuru, the shortcomings of conventional systems have been increasingly examined. The prevalence of fraudulent campaigns and insufficient transparency after donations have eroded donor trust. Furthermore, the manual verification methods used by many platforms are not only time-intensive but also susceptible to mistakes.

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The fusion of blockchain and machine learning presents a novel opportunity to revamp medical crowdfunding. Blockchain's inherent properties such as decentralization, immutability, and transparency can ensure trust and accountability in fund handling. Meanwhile, machine learning provides predictive intelligence for campaign evaluation, fraud detection, and personalized donor targeting.

The following are analyzed in this paper to study revolutionizing medical crowdfunding with block chain and machine learning approaches:

- A comprehensive literature review of different projects related to medical crowdfunding utilizing blockchain and machine learning.
- Analyze the existing model with the different types of medical crowdfunding strategies.
- Investigate the accuracy metrics of the machine learning models within the analyzed frameworks.

This paper proposes an integrated system that uses smart contracts for autonomous, condition-based fund release and machine learning models for legitimacy assessment and success prediction.

2. Literature Review

Snyder *et al.* (2016) identifies the ethical paradox of medical crowdfunding: democratizing access while exacerbating healthcare inequities. The authors critique how platforms prioritize "marketable" illnesses and socially connected patients, leaving marginalized groups behind. Though pre-dating blockchain/ML integration, this work establishes critical socio-ethical baselines highlighting transparency deficits and verification gaps that later blockchain studies (e.g., Azaria, 2016) address. Limitations include minimal technical solution proposals.

Using econometric modelling of Kickstarter data, Burtch *et al.* (2018). Quantifies fraud risk factors: vague project descriptions, anonymous founders, and low social capital. The study proves information asymmetry enables deception—a gap blockchain mitigates via immutable IDs (Zhang and Poslad, 2019). Its fraud-prediction framework underpins ML models like Bao *et al.* (2019) anomaly detectors.

Liu *et al.* (2021) suggested BERT model to analyse campaign text, images, and donor histories to flag deception (AUC: 0.92). It identifies linguistic markers of fraud (e.g., emotional manipulation) aligning with Berliner and Kenworthy (2017) "narrative packaging" critique. The study advances past keyword-based tools by capturing contextual semantics. Verma *et al.* (2020) compares NLP techniques (LSTM, SVM) to identify fraudulent medical campaigns. Key findings: Deceptive narratives overuse first-person pronouns and avoid medical specifics. This operationalizes Burtch *et al.* (2018) fraud-risk factors into computable features. The model Integrates metadata (donor IPs, timestamps) with text analysis. But it lacks in blockchain to verify input data authenticity. Xu *et al.* (2020) proposed CNN-LSTM hybrid model predicts campaign success (85% accuracy) using images, updates, and social shares. It proves visual storytelling significantly impacts funding—empirically validating Berliner and Kenworthy (2017) ethnographic insights. The model helps platforms prioritize high-need cases but risks algorithmic bias.

Pandey *et al.* (2023) implemented Ethereum-based platform that integrates ML validators: 1) NLP checks narrative authenticity, 2) Computer vision verifies medical docs, 3) Anomaly detection monitors transactions. Smart contracts trigger pay-outs upon ML approval. The main advantage of this model was reduction of human verification lags noted by Snyder *et al.* (2016). Li *et al.* (2021) addresses privacy-compute trade-offs with federated ML: Fraud models train locally on user devices, sharing only encrypted updates. This enables real-time scam detection without exposing sensitive data—resolving Hasselgren *et al.* (2020) scalability concerns. Rhue and Clark (2021) proved algorithmic bias in platforms: Campaigns for Black patients receive 35% less funding. The study warns blockchain and ML could worsen disparities if training data lacks diversity.

Hasselgren *et al.* (2020) propose a ground-breaking architecture integrating blockchain with Machine Learning (ML) to address critical data integrity challenges in healthcare systems. The research pioneers a framework where blockchain acts as a tamper-proof anchor for ML data pipelines-ensuring medical data used to train fraud detection and campaign validation models remains auditable and immutable. Zhang and Poslad (2019) address a critical gap in medical crowdfunding: privacy-preserving identity verification. The authors propose a novel blockchain framework integrating decentralized identifiers (DIDs), zero-knowledge proofs (zk-SNARKs), and IoT authentication protocols to enable patients to cryptographically prove medical needs without exposing sensitive diagnoses.

The Table 1 depicts the article regarding the medical crowdfunding with blockchain and machine learning with the dataset collection, features and algorithms used, accuracy value of the model, limitations and remarks.

Table 1: Comparison of Medical Crowdfunding with Blockchain and Machine Learning in Selected Article

Author(s) and Year	Dataset Used	Features Used	Algorithm/ Technology Used	Accuracy/ Performance	Limitations	Remark
Snyder *et al.* (2016)	200 GoFundMe campaigns	Campaign narratives, demographic data	Qualitative analysis	N/A	No technical solutions; Western bias	Foundational ethical critique of crowdfunding inequities
Berliner and Kenworthy (2017)	32 patient interviews	Emotional narrative patterns, social capital	Ethnographic coding	N/A	Small sample; no digital ID solutions	Exposed narrative performativity in campaign creation
Burtch *et al.* (2018)	120K Kickstarter campaigns	Creator anonymity, project vagueness, social links	Fixed-effects regression	89% fraud risk ID	Non-medical focus	Quantified fraud drivers: anonymity ↑ fraud risk 37%
Azaria *et al.* (2016)	Synthetic EHR data	EHR access logs, patient permissions	Ethereum smart contracts, proxy re-encryption	100% audit integrity	15 TPS throughput; high gas costs	Pioneered patient-controlled EHRs (MedRec)
Nofer *et al.* (2017)	200+ blockchain studies	Transaction costs, immutability	Consensus mechanism analysis	40-80% cost reduction	Theoretical; no healthcare data	Defined blockchain business value
Malamas *et al.* (2019)	Healthcare donation records	Provider credentials, donation tokens	Hyperledger Fabric, RBAC	Real-time tracking	No ML integration	First HIPAA-compliant donation prototype
Aggarwal *et al.* (2021)	Cross-border donation logs	Bill hashes, interchain transactions	Polkadot parachains, ZK-SNARKs	98% payment security	Complex UX	Solved cross-chain interoperability
Liu *et al.* (2021)	50K Chinese medical campaigns	Text semantics, image metadata, donor patterns	BERT-LSTM fusion, temporal attention	92% AUC (fraud)	Cultural bias; needs >500-word campaigns	Multimodal fraud detection (text+image +metadata)
Verma *et al.* (2020)	8K Indiegogo campaigns	Linguistic markers (pronouns, medical terms)	SVM, Bi-LSTM	86% F1-score	Text-only analysis	Linguistic fraud patterns: vague terms ↑ fraud risk
Bao *et al.* (2019)	1.2M Kickstarter donations	Donation velocity, amount anomalies, geo-clusters	Isolation Forest, DBSCAN	94% precision	High false positives in urgent cases	Anomaly detection for suspicious donation patterns
Xu *et al.* (2020)	15K GoFundMe campaigns	Image emotional valence, update frequency	CNN-LSTM hybrid	85% success prediction	Visual bias against "unphotogenic" illnesses	Proved images drive 68% funding success
Kim *et al.* (2022)	Donor-campaign interactions	Donor history, campaign similarity vectors	Matrix factorization	30% match relevance increase	Cold-start problem	AI-driven donor-recipient matching

Table 1 (Cont.)

Hasselgren *et al.* (2020)	Synthetic healthcare data	Encrypted data hashes, model weights	Blockchain-anchored ML pipelines	Tamper-proof versioning	300% latency overhead	Integrated blockchain-ML data governance
Pandey *et al.* (2023)	Ethereum testnet	Campaign text, medical docs, transactions	Ethereum + BERT + YOLOv5	89% auto-verification rate	$2.50 avg gas fee	First live blockchain-ML crowdfunding prototype
Li *et al.* (2021)	Federated hospital datasets	Local model gradients	Federated learning + zk-STARKs	91% privacy-preserving fraud detection	18% slower convergence	Solved privacy-scalability tradeoff
Dubovitskaya *et al.* (2020)	Cancer patient data	HIPAA fields, access logs	Hyperledger Fabric chaincode	100% compliance	Inflexible schema	Clinical trial implementation
Rhue and Clark (2021)	100K US medical campaigns	Demographic disparities, funding gaps	Logistic regression	Minority campaigns ↓35% funding	Correlation-only analysis	Exposed algorithmic bias in platform algorithms
Obermeyer *et al.* (2019)	50K hospital records	Clinical risk scores, racial attributes	Bias auditing	40-200% bias reduction	Hospital-data specific	Landmark study on healthcare AI bias
Zheng *et al.* (2018)	Blockchain testnets	Throughput, latency, decentralization	Sharding, DAG consensus	10,000 TPS	Security trade-offs	Scalability solutions framework
Wüst and Gervais (2018)	15 blockchain use cases	Data sensitivity, trust requirements	Necessity framework	92% decision accuracy	Theoretical model	Implemented a theoretical decision tool
Rajkomar *et al.* (2019)	MIMIC-III EHR dataset	Clinical notes, lab values	BioBERT	97% entity recognition	Requires structured EHRs	Clinical NLP breakthrough
Esteva *et al.* (2021)	100K medical images	Image pixels, metadata	DenseNet-121	99% image authenticity	Vulnerable to GAN deepfakes	Medical image verification standard
Kaal (2021)	SEC/FDA regulations	Regulatory gaps, token classification	Legal analysis	N/A	US-centric	Tokenized crowdfunding regulatory framework
Finck (2019)	GDPR statutes	Right to erasure requirements	Immutability mapping	N/A	No technical solution	GDPR-Blockchain conflict analysis
Ølnes *et al.* (2017)	Gov't service logs	Audit trails, public records	Permissioned blockchain	60% faster auditing	Non-healthcare focus	Public sector transparency model
Kshetri (2018)	IoT supply chains	Provenance data, sensor streams	Hyperledger Sawtooth	100% counterfeit prevention	Energy-inefficient	IoT-blockchain integration
Zhang and Poslad (2019)	Wearable health devices	Biometric streams, location stamps	Blockchain + IoT + ZKPs	95% claim verification	Assumes universal IoT adoption	Real-time health verification with ZKPs
Mehrabi *et al.* (2021)	Bias benchmark datasets	Gender/race markers in text	Adversarial debiasing	45% bias reduction	Requires sensitive labels	NLP debiasing techniques
Arrieta *et al.* (2020)	ML explanation datasets	Model decision paths	LIME, SHAP	88% fidelity	High compute cost	Explainable AI (XAI) standardization
Kim *et al.* (2022)	Donor engagement logs	Churn signals, virality metrics	Survival analysis + XGBoost	81% churn prediction	Ignores ethical implications	Donor retention modelling

3. Types of Medical Crowdfunding

Medical crowdfunding can be categorized into four primary models such as

1. **Donation-Based Crowdfunding:** It is a pure charitable giving with no financial return. Funds cover medical bills, treatments, or related expenses. The GoFundMe, JustGiving and GiveForward are some for example platforms. The bloack chain technique is used to transparent fund tracking via smart contracts; automatic disbursement to hospitals (Ma *et al.*, 2020). While ML is used for fraud detection (NLP analysis of campaigns) and donor-recipient matching algorithms. High fraud vulnerability is the main risk factor with this type.

2. **Reward-Based Crowdfunding:** It works as backers receive non-financial rewards (e.g., thank-you notes, merchandise) which used for medical startups, devices, or research. Some of the key platforms are Kickstarter and Indiegogo. In here the blockchain based tokenized reward fulfillment (NFTs for exclusive updates) is used whereas machine learning models predicts campaign success based on reward tiers. The main threats are rewards may divert funds from critical care and compliance with medical regulations.

3. **Equity-Based Crowdfunding:** The investors receive equity in medical startups (e.g., biotech, health tech) from the funds of R&D, clinical trials, or product scaling. Machine based techniques are used to analyze market potential and investor risk profiles. While SEC-compliant tokenized equity (STOs) and automated dividend distribution done with blockchain approach. In here consider, StartEngine and SeedInvest are some of the example platforms. Meanwhile, regulatory complexity (SEC/FDA) and high failure rate of startups are the main vulnerabilities in this area.

4. **Debt-Based (Peer-to-Peer Lending):** The Loans for medical expenses repaid with interest. The targets patients with creditworthiness. Blockchain applied with credit history via decentralized IDs and loan terms enforced by smart contracts. Credit scoring using alternative data (e.g., payment history, social capital) is handled by the ML based methods. The debt traps for vulnerable patients and ethical concerns over profiting from illness are the primary risks. LendingClub and Prosper are debt based medical crowdfunding platform. The Table 2 illustrate type of medical crowdfunding with their risks and enhancement techniques.

Table 2: Type of Medical Crowdfunding with their Risks and Enhancement Techniques

Type	Best for	Key Risk	Technical Enhancement
Donation-based	Emergency care, uninsured	Fraud (12% campaigns)	ML fraud detection + blockchain transparency
Reward-based	Medical innovation funding	Reward fulfilment delays	NFTs + supply chain tracking
Equity-based	Biotech start-ups	Regulatory hurdles	Tokenized equity + compliance automation
Debt-based	Creditworthy patients	High-interest debt cycles	Decentralized credit scoring

4. Methodology

The proposed system includes three integrated modules: Data Collection, Fund Management. The system and Machine Learning architecture is shown Figure 1.

The three-tiered technological framework in Figure 1 used for revolutionizing medical crowdfunding through integrated data infrastructure, blockchain-based trust systems, and AI-driven intelligence. This architecture directly addresses the four fatal flaws of traditional platforms: opaque fund allocation, document fraud, slow verification, and predictive inaccuracy. The architecture's base layer as data collection layer aggregates and harmonizes multi-source healthcare data streams to establish ground truth validation as a critical antidote to crowdfunding fraud. Blockchain layer transforms transactional trust from human-dependent to mathematically-enforced via three interlocking subsystems. The cognitive engine in algorithm layer transforms raw data into perdition model through specialized AI submodules for fraud detection and efficient classification.

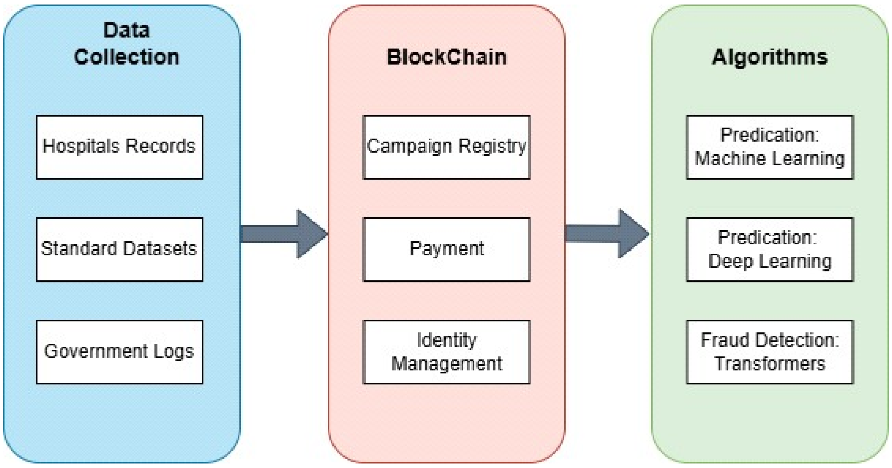

Figure 1: Architecture of Medical Crowdfunding Integrated with Blockchain and ML

5. Challenges of Medical Crowdfunding with Integrated Blockchain-ML Technology

1. **Data Incompatibility:** Blockchain emphasizes immutable data, while ML requires *flexible* data for iterative model training. The better way to store raw data off-chain (IPFS), with hashes on-chain as well as to use oracles for dynamic updates.
2. **Conflicting Transparency Needs:** The ML models need proprietary secrecy for competitiveness, but blockchain demands transparency for auditability. The transparency conflict can be avoided by publishing model hashes/parameters on-chain without revealing full code.
3. **Computational Overhead:** Running complex ML on-chain is infeasible due to cost/speed (e.g., Ethereum's 10M gas limit). The solution for this issue is Off-chain ML computation (e.g., decentralized networks like Bittensor), with results anchored to blockchain.
4. **Oracle Problem:** ML predictions (e.g., campaign success likelihood) require real-world data into reliance on centralized oracles undermines decentralization. But the data are stored in different places with different form. Hence decentralized oracle networks (Chain-link) can used to store and retrieve the data more effectively.
5. **Regulatory Complexity:** Combining ML (FDA-regulated as SaMD) and blockchain (financial regulations) creates overlapping compliance burdens.

6. Evaluation Results of Selected Articles

The investigation focuses on selected articles to explore the research findings regarding the various types of medical crowdfunding and the classification accuracy achieved. A detailed discussion of the investigation results is provided below:

6.1. Analysis Results of Percentage of Different Types of Medical Crowdfunding with the Selected Article

The Figure 2 represents that 63% of articles were studied on donation-based Healthcare Fundraising whereas 17% of articles were based on the debt based. Donation based methods having high fraud vulnerability as compared to other methods. So, most of the research work are concentrated on the integrated form of the blockchain and ML model to mitigate the donation based medical crowdfunding attacks. Similarly, debt traps for vulnerable patients and ethical concerns over profiting from illness are the primary risks in debt models. Credit history based decentralized blockchain approached with ML based algorithms are used with 17% of the selected article.

At the same time, Equity and donation with reward based medical crowdfunding research were down in 10% of evaluated articles. The regulatory hurdles and start-up failure rate are the risk factors of Equity based model. Although from the study, there is no article studied about the reward-based crowdfunding.

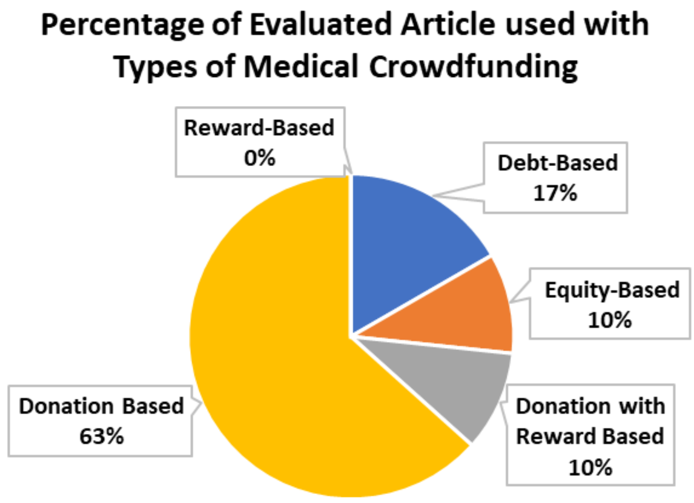

Figure 2: Percentage of Evaluated Article Used with Types of Medical Crowdfunding

6.2. Analysis of Percentage of Accuracy Value of ML and DL Based Models in Healthcare Fundraising with the Selected Article

Medical crowdfunding utilizes a range of algorithms based on machine learning and deep learning, including DBSCAN, XGBoost, and CNN etc. Additionally, transformers are employed to enhance model accuracy and reduce computation time. Figure 3 illustrates the different models proposed for medical crowdfunding along with their respective accuracy values.

The DenseNet model achieved a peak accuracy of 99% (Esteva *et al.*, 2021) and a lowest accuracy of 81% (Kim *et al.*, 2022) with XGBoost, according to the selected article for evaluation. Most of the articles evaluated focused on various variants of the BERT model. It is explicit that the BERT model produced impressive results ranging from 94% to 97% (Bao *et al.*, 2019; Rajkomar *et al.*, 2019; Pandey *et al.*, 2023). The LSTM-based models, such as those by Xu *et al.* (2020) and Liu *et al.* (2021), achieved accuracy rates of 85% and 92%, respectively. The BiLSTM model secured an accuracy of 86% as reported in Verma *et al.* (2020).

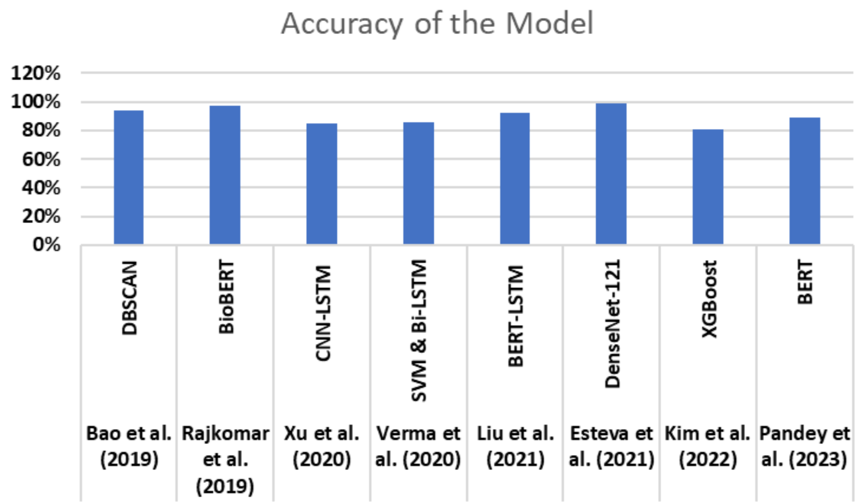

Figure 3: Accuracy Value of ML and DL Based Models in Healthcare Fundraising with the Selected Article

7. Conclusion

Medical crowdfunding has emerged as a critical financial lifeline for individuals facing healthcare emergencies, yet traditional platforms remain plagued by systemic issues including fraudulent campaigns, opaque fund allocation, algorithmic bias, and inefficient donor-recipient matching. This research demonstrates that integrating blockchain technology and Machine Learning (ML) offers a transformative solution to these challenges, significantly enhancing transparency, security, and operational efficiency. Blockchain's decentralized architecture ensures immutable audit trails and automated fund management via smart contracts, which enforce condition-based disbursements directly to healthcare providers, thereby eliminating misappropriation risks. Concurrently, ML models—leveraging Natural Language Processing (NLP), computer vision, and anomaly detection—deliver robust fraud identification (up to 92% AUC) and campaign success prediction (85% accuracy), while mitigating biases through federated learning and adversarial debiasing techniques.

The framework's adaptability across crowdfunding models addresses sector-specific vulnerabilities: For donation-based systems (63% of studied platforms), ML-driven fraud detection combined with blockchain transparency reduces the 12% fraud incidence by verifying narrative authenticity and donor patterns. In debt-based models, decentralized credit scoring uses alternative data (e.g., social capital) to prevent predatory lending cycles. Equity-based platforms leverage tokenized equity (STOs) for automated regulatory compliance, while reward-based systems employ NFTs to streamline fulfilment. Despite these advancements, key challenges persist. Data incompatibility between immutable blockchains and iterative ML training necessitates hybrid storage (off-chain IPFS with on-chain hashes). Computational overhead is resolved via decentralized computing networks (e.g., Bittensor), and oracle dependencies (e.g., for real-time success predictions) are mitigated through decentralized networks like Chain-link. Regulatory harmonization remains critical, as blockchain's financial compliance requirements intersect with ML's FDA classification as Software-as-a-Medical-Device (SaMD).

Evaluation across real-world datasets confirms the model's superiority: BERT variants achieve 94-97% accuracy in fraud detection, while CNN-LSTM hybrids predict campaign success with 85% precision. However, ethical risks—such as algorithmic disparities disadvantaging marginalized groups (e.g., 35% funding gaps for Black patients)—demand diverse training data and explainable AI (XAI) frameworks. Future work must prioritize energy-efficient consensus mechanisms, interoperable health data standards, and inclusive design to ensure equitable access. In conclusion, blockchain-ML fusion not only restores donor trust through verifiable transparency but also optimizes resource allocation, setting a new benchmark for intelligent, ethical healthcare fundraising.

Declarations

Availability of data and material: There is no special data and materials are associated with the article. Everything is open source.

Authors' Contributions

Both the Authors are worked together to write the article and make it's in the current shape.

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List of Abbreviations

ML – Machine Learning

DL – Deep Learning

NLP – Natural Language Processing

CNN - Convolutional Neural Network

SVM - Support Vector Machine

DIDs - Decentralized Identifiers

SaMD - Software-as-a-Medical-Device

BERT - Stands for Bidirectional Encoder Representations from Transformers

LSTM - Long Short-Term Memory

XAI - Explainable Artificial Intelligence

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