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Hybrid AI Ensemble and Blockchain-Based Chatbot for Decentralized Toddler Nutritional Status Classification

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Abstract: The accurate and timely classification of toddlers' nutritional status is critical for early intervention, particularly in remote or underserved communities with limited access to healthcare professionals. However, data security, especially for children's health data, is equally essential to ensure safe storage and access. To address these challenges, this study proposes a hybrid AI-powered chatbot that integrates ensemble learning, blockchain, and decentralized storage to support both nutritional status classification and educational interaction. The system combines a random forest model for classification with GPT-3.5 Turbo for bilingual (Indonesian–English) stunting education deployed via Telegram. Preprocessing includes standardizing, normalizing, and encoding Indonesian-language nutrition data to ensure machine learning readiness. Six ensemble algorithms are evaluated using stratified five-fold cross-validation, with classification results hashed using SHA-256 and immutably stored on the Interplanetary File System (IPFS) and a local Ethereum blockchain. The chatbot effectively manages both structured inputs and natural language queries, ensuring secure, transparent, and real-time nutritional assessments. Results demonstrate high classification performance, with the random forest model achieving the highest mean F1-score (0.9987) and the lowest deviation. Its robustness was validated by a 20% hold-out test set and stratified five-fold cross-validation, which obtained excellent balanced performance across nutritional status categories (F1-macro, precision, recall, accuracy ≈ 0.99; ROC AUC = 1.00). External validation also yielded robust and consistent results (F1-macro = 0.97, precision = 0.97, recall = 0.96, ROC AUC = 0.98, and accuracy = 0.97), demonstrating the model's generalization ability and mitigating concerns regarding overfitting. Blockchain evaluation confirmed stable and linear CID transaction throughput (blocks 29–46) with no observed latency, ensuring reliable and continuous data recording. Furthermore, gas prices decreased by ~87.5%, highlighting significant improvements in cost efficiency and scalability, which reinforces blockchain's feasibility for decentralized, AI-driven health data management.

Keywords: chatbot, AI ensemble, Ethereum, healthcare, IPFS, CID, SHA-256

1. Introduction

The precise and timely identification of toddlers' nutritional condition is vital for effective intervention. Existing approaches (non-inclusive) continue to be associated with centralized models, manual techniques, and constrained healthcare professional access [1, 2]. These constraints hinder diagnoses and action, most significantly in far-off and underprivileged communities. To overcome these limitations, AI offers potential solutions through automated classification systems that can accurately understand nutritional information.

The rise of AI chatbots has brought about numerous innovative changes in the healthcare sector, particularly in real-time health support [3], predictive diagnostics, and early warning systems [4–6]. AI-powered chatbots are new intelligent systems that provide aid to both patients and medical professionals [7–9]. These systems analyze symptoms, provide health advice, and predict health conditions using natural language processing (NLP) and machine learning models [10–12]. Ensemble learning, which integrates multiple learning algorithms, is recognized for increasing prediction and classification accuracy by reducing biases and strengthening generalization [13–15]. In addition, chatbots are convenient and scalable agents that bring real-time, personalized interaction to caregivers, even in the absence of professional supervision.

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For example, the most recent AI models for training chatbots, such as the Generative Pre-trained Transformer (GPT), have been utilized in healthcare dialog systems. They have demonstrated impressive results in tasks such as disease detection, diagnosis, and classification [16–18]. At the same time, blockchain technology has introduced a new model for healthcare databases by supporting an immutable, transparent, and tamper-evident record of healthcare activity. Toward this goal, in the healthcare sector, disciplined patient data exchange and management based on Ethereum smart contracts provide a secure, transparent, and auditable framework to ensure the integrity of shared medical records [19–21]. This is particularly important when protecting sensitive health information relating to children, which must meet the highest standards in terms of accuracy and auditability.

In addition to blockchain, decentralized storage systems such as the Interplanetary File System (IPFS) offer a desirable option for storing medical records. IPFS serves as a distributed file storage and retrieval system to avoid a single point of failure and prevent data breaches [22–24]. It is also proposed that having content identifiers (CIDs)—hashed with multihash-256 and Base58—increases data security and data traceability [25]. CIDs generate a unique fingerprint of each data file and store it as a tamper-resistant reference, which can be referenced and validated easily through distributed networks [26, 27].

Nevertheless, the integrity, transparency, and user control of personal health-related data are essential. Blockchain brings us closer to solving these issues by providing trustworthy, decentralized storage and traceability. Combining blockchain with AI chatbots can lead

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to a decentralized system capable of classifying nutritional status, safeguarding health information, and facilitating secure user interaction. In this paper, a hybrid AI ensemble learning–blockchain-based system designed to classify toddlers' nutritional status is presented.

The objective of the proposed system is to provide caregivers with real-time, accurate nutritional status classification while ensuring data security and availability, particularly in areas where healthcare is not well established. The random forest model is based on age, gender, and height as independent predictors for nutritional status prediction. Classification predictions are communicated to users through a Telegram chatbot, which also incorporates GPT-3.5 Turbo for interactive classification of nutritional status. The user model is stored permanently in a local Ethereum network (Ganache) via smart contracts, ensuring the integrity and authenticity of the stored data. The records are hashed with SHA-256 and Base58-encoded, saved on IPFS, and linked with CIDs. Such a system design enhances predictability and accuracy in toddler health data management, thereby ensuring open-source, decentralized, and tamper-resistant health control systems for toddlers.

2. Literature Review

Babu and Boddu [28] proposed a bidirectional encoder representation from a Transformer (BERT)-based model to develop a healthcare chatbot that aims to improve health communication, which is generally characterized by naive or undirected language, an inexperienced understanding of chatbot responses, and a lack of personalization. The proposed chatbot has shown impressive performance (98% accuracy, 97% precision, 97% ROC AUC, 96% recall, and 98% F1-score). Unfortunately, such an approach aims only to improve conversational accuracy and the prediction aspect. At the same time, it does not incorporate blockchain to create transparent or secure data nor does it deploy decentralized storage for tamper-proof health records.

Chakraborty et al. [29] presented a deep feedforward multilayer perceptron model to predict and interact with an AI-based chatbot for medical purposes to promote user awareness and disease prevention with a testing accuracy of 94.32%. Nevertheless, only the chatbot's interaction and prediction are urged without considering the vital data's security issues and accountability transparency, which means how it works in a decentralized manner. It also does not incorporate blockchain applications and advanced explainability strategies, and a focus on the application aimed at vulnerable groups is missing.

Muneer et al. [30] proposed a chatbot supported by blockchain-based explainable AI (XAI) for explicating video readings and a decision-making system assisting in making a responsible decision in CVD screening with an accuracy of 97.12%. They highlighted the secure management of healthcare data using decentralized blockchain technology. Nonetheless, even though the research considers AI, blockchain, and XAI, it focuses more on diagnostic challenges within a specialized scope (CVD care), rather than on processes, interactive multilingual education, and end-user storage on a distributed level. In addition, it does not demonstrate users' integration with friendly communication architectures or address the larger issues of community-based public health surveillance.

Almazroi [31] introduced an integrated model called EffiIncepNet for healthcare data classification by combining EfficientNet and Inception-ResNet-v2 based on a blockchain-equipped anomaly detection and fraud prevention framework. The system is constructed using wearable sensors, deep learning for classification, and a multinode blockchain structure to enhance security and scalability in medical data management. However, the model lacks real-time, user-facing interaction and features, which restricts its application to decentralized, community-based concepts. On the other hand, the work that we present here involves a hybrid AI-based chatbot integrated with an ensemble-based learning methodology for classifying toddler nutrition. The system design utilizes GPT-3.5 Turbo to enhance health education, which is being rolled out on Telegram. It improves transparency and trust by storing the hash on Ethereum, utilizing Base58 for encoding, and integrating Ethereum with IPFS, thereby providing a transparent and explainable solution suitable for early-stage use in vulnerable populations.

Fenta et al. [32] developed a machine learning model to identify the determinants of chronic undernutrition among children in Ethiopia's administrative zones. They suggested an ensemble of multiple ML models trained on retrospective national health survey data from 2000, 2005, 2011, and 2016. Their strategy involved six machine learning classifiers, including random forests, to assess prediction performance using accuracy, sensitivity, specificity, and AUC scores. The approach focused on demographic and geographic characteristics, including parental literacy, settlement type, and place of residence. Empirical evaluations demonstrated that the random forest model outperformed other models in terms of all employed metrics and successfully identified high-risk areas in northern Ethiopia. This method, however, should be integrated with real-time prediction of punctuality to achieve optimal decision-making effects on nutrition monitoring systems.

Bitew et al. [33] developed a predictive model of child undernutrition among children under five in Ethiopia based on machine learning methods to find important predictions and estimate contributions of sociodemographic covariates. They developed a model that combines five individual models—XGBoost, KNN, random forests, neural networks, and GLM—to predict child stunting using 2016 Ethiopian Demographic and Health Survey data. Their suggested approach focused on regional differences and household-level predictors of malnutrition outcomes. Empirical results: The researchers compared XGBoost with other methods and found that XGBoost consistently outperformed the others, providing evidence that it is a powerful model for prediction across all outcomes. This model identified significant predictors, including access to water, a history of anemia, the child's age, small birth size, and the mother's underweight status. Nonetheless, the present study requires further refinement for real-time application and incorporation into a decision-making system for targeted nutrition interventions.

Maasthi et al. [34] developed a decision support system for the prediction and prevention of malnutrition and anemia using different machine learning algorithms and nutrition-related datasets. They established a linkage model to analyze malnutrition among children under five and adults aged 15 years and older. They then provided predicted recommendations for dietary intake to prevent these diseases using historical health records. They utilized a set of classification models, including NBC, DT, RF, and K-nearest neighbor (KNN), in their study to compare predictive accuracy. Naïve Bayes and random forest demonstrated the most efficient results in classifying syndromes, including malnutrition and anemia, with reported accuracies of 94.47%, 85%, 95.49%, and 63.15%, respectively. Although it presented high predictive accuracy, the system lacked attributes such as distributed data control, online classification, and individualized user interaction. However, their system was not based on blockchain for secure, decentralized storage, and it did not employ a chatbot interface for interactive nutritional assistance either. Furthermore, the lack of ensemble learning in the model would weaken its robustness and generalization, particularly in underserved or isolated regions, where decentralized AI assistance is increasingly required.

Akseer et al. [35] developed an approach combining qualitative and quantitative evidence to examine the multifaceted influences on successful stunting reduction, focusing on the reduction of child stunting in several exemplary countries. They formulated an analytical protocol and research standards that incorporated both qualitative and quantitative components (policy analysis, literature review, semistructured interviews, and statistical modeling). Their approach included consultation with stakeholders and expert technical advisers, as well as case studies for direct community engagement to explore the context-specific advances in nutrition. The research employed an integrative approach at the system level, triangulating different sources of data and drawing on the evidence base of PRIME to inform national policy narratives. Although this holistic model yields important macroscale insights, it lacks real-time prediction, microscale classification, and interactive support systems. Their approach does not encompass AI-based classification, data security for scattered data, or chatbot-based nutrition education to support caregivers at the community level directly.

Hasdyna et al. [36] developed a hybrid machine learning approach to deal with the problems of classification, prediction, and clustering of stunting prevalence in Aceh, a province of Indonesia. Their proposed combined support vector machine model, which employed both RBF and sigmoid kernels, obtained a classification accuracy of 91.3%. The RBF kernel dominated over the sigmoid kernel. In addition, their system utilizes linear regression to predict future trends, achieving a very low mean squared error (MSE) value of 0.137. It employed a weighted-product model for optimizing K-Medoids clustering, thereby increasing the efficiency of clustering and enhancing cluster quality. This approach provided rapid decision-making advice to target the high-risk population, and the analysis results helped in informing the creation of effective public health policies. However, the system lacks key components, including interactive feedback, decentralized deployment, and real-time availability.

In addition to these, this study introduces a new hybrid AI ensemble-blockchain-based chatbot system for the decentralized classification of toddler nutritional status. A random forest classification algorithm is implemented in the system, allowing for the assessment of nutritional status using input features such as age, gender, and height. The user will see the classification results directly in the Telegram chatbot interface, which also helps GPT-3.5 Turbo deliver engaging educational content on nutrition advice and stunting. The classification results are written to a private Ethereum blockchain using smart contracts for tamper-proof logging. At the same time, the outcome will persist on IPFS as an encrypted JSON file, containing the SHA-256 hash wrapped in a multihash-256 and Base58-encoded version of the hash, along with a unique URL (CID) to ensure that the content can always be found through a decentralized system. This also helps in fulfilling the growing demand for accurate classification and transparent processing of health data, as well as for an interactive educational environment on an integrated platform.

To clarify the methodological underpinnings, this study compares various model approaches commonly used for classifying nutritional status. Table 1 summarizes the advantages, limitations, and relevance of each approach. The primary focus of this study is on the ensemble learning method due to its higher interpretability, relatively low computational requirements, and suitability for handling unbalanced datasets [37]. In contrast, neural network-based approaches and multimodal architectures have greater potential to capture complex patterns but require larger multimodal datasets, higher computational costs, and lower transparency [38, 39]. This comparison confirms that the choice of ensemble methods aligns with the health context, which demands transparency, resource efficiency, and ease of adoption in real-world practice.

3. Proposed Methodology

The proposed model is presented in Figure 1. The steps for the proposed model will be described in the following subsection. Figure 1 illustrates the hybrid AI and blockchain-based chatbot model for classifying and educating toddlers' nutrition. It integrates Telegram input, random forest, GPT, IPFS, and the Ethereum blockchain to enable secure and auditable data management. Users communicate with the chatbot via the Telegram API, and the input data are processed within a Python-based virtual environment. This environment integrates GPT for educational conversations, a prompt dialog to guide the flow of interaction and minimize unsafe responses, and a random forest classifier for nutritional status classification. To ensure reliability, the GPT component is grounded with authoritative health references, including WHO guidelines, the Indonesian Ministry of Health regulations, and the 2019 Nutritional Adequacy Rate (AKG). Features are detected, and the optimal classifier is selected using preprocessing, cross-validation, and training (the toddler dataset). The classification results are serialized, saved to IPFS, hashed using SHA-256, and committed to a local Ethereum blockchain for immutability, auditability, and secure data retention.

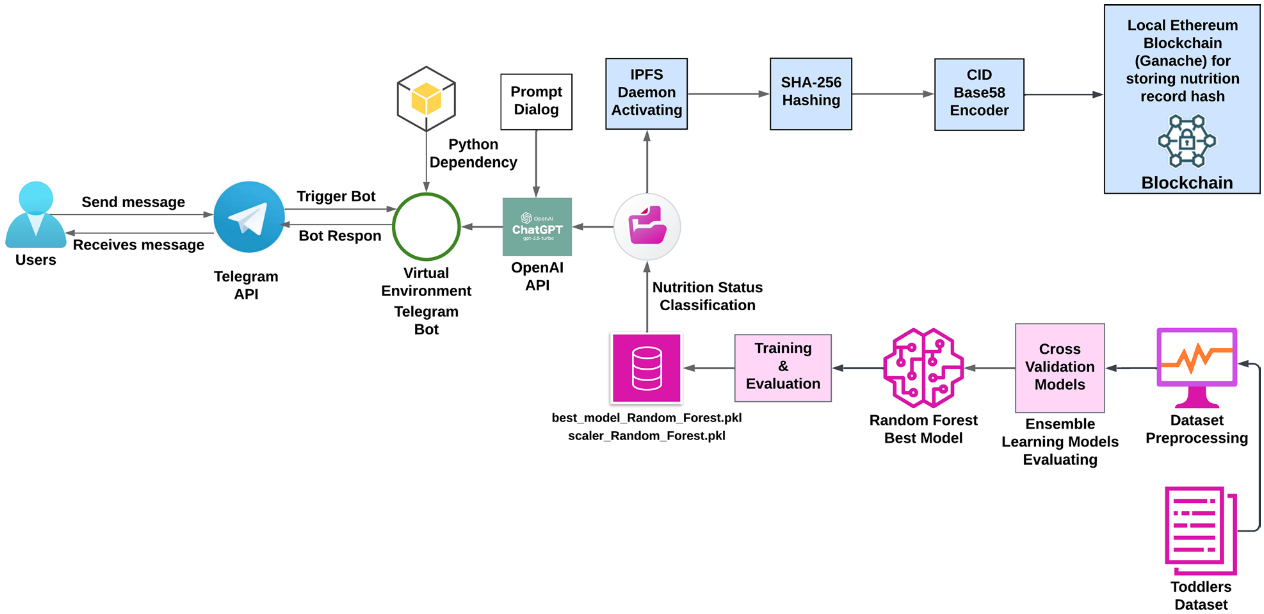
3.1. Dataset description

In this study, the dataset used was "Stunting Detection" from Kaggle, which comprised approximately 121,000 entries. Each entry included four main variables: age (0–60 months), gender (boy/girl), height (cm), and nutritional status. Nutritional status is categorized into four classes: severely stunted (<−3 SD), stunted (−3 SD to <−2 SD), normal (−2 SD to +3 SD), and tall (>+3 SD) based on the WHO z-score standard [40]. This dataset has undergone preprocessing to ensure quality and consistency before use in classification experiments. This dataset is available in a CSV file titled "stunting_dataset.csv." The first column contains gender, the second column contains age (months), the third column contains height (cm), and the fourth column contains nutritional status categories, namely, "normal," "stunted," "severely stunted," and "tall." The datasets are illustrated in Table 1. Although this dataset provides valuable insights and was created according to WHO

Table 1
Comparison of model approaches for nutritional status classification

Model approach	Advantages	Limitations	Relevance to healthcare context
Ensemble methods (random forest, XGBoost, LightGBM, etc.)	• Relatively good interpretability • Reduced computation cost • Admissible for imbalanced databases	Less capable of capturing multimodal patterns	Aligns with healthcare needs: transparency and resource efficiency
Neural networks (attention-based, CNNs, etc.)	• Can capture complex and non-linear patterns • Suitable for multimodal data	• Require multimodal data • High integration complexity	Less suitable for limited anthropometric datasets but promising for future studies
Hybrid/multimodal models (e.g., clustering-AI + anthropometry + food images)	• Integration of diverse data sources • Potential to improve generalizability	• Require multimodal data • High integration complexity	Appropriate for long-term development using clinical and community data

Figure 1
Proposed AI-blockchain chatbot architecture for toddler nutritional status classification and education



criteria, it is not collected directly from clinical or field measurements.

In addition to the primary dataset, this study uses external Kaggle datasets that include variables such as gender, age, and height, as well as nutritional status labels. This dataset is used for external validation to evaluate the generalization capabilities of the proposed model across various data sources. As a result, these data may lack diversity in socioeconomic, regional, and ethnic representation, limiting their generalizability to real-world populations. To address these limitations, future research will combine clinical and community-based datasets for broader validation and application. The datasets are illustrated in Table 2.

Table 2 shows an example of four records from the toddler database that report age in months, gender, height (cm), and nutritional status categories. The categories of physical development, such as "stunted," "tall," and "severely stunted," are used to illustrate the differences between them.

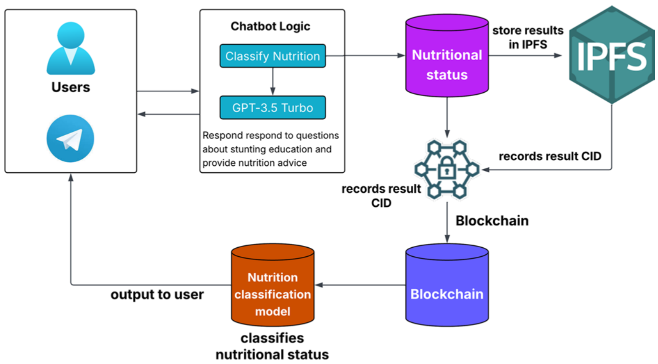
Table 2
Dataset description

No.	Age (months)	Gender	Height (cm)	Nutritional status
1	12	Boy	64.6	Severely stunted
2	12	Boy	84.5	Tall
3	11	Girl	64	Severely stunted
4	11	Girl	67.2	Stunted

3.2. Architecture of the AI-blockchain chatbot system

The architecture shown in Figure 2 employs a procedural, modular approach to ensure accurate classification, enhance user interaction, and maintain data security. Users interact with the system via the Telegram interface by sending anthropometric data, both in structured form and as free text, for the classification of nutritional status. They can also ask questions related to stunting education. The chatbot's logic then determines the appropriate processing flow. For classification requests,

Figure 2
Blockchain-integrated AI chatbot system for secure toddler nutritional status classification and data management



data are processed by a nutritional status classification model trained and validated using the random forest ensemble method, which enables it to predict children's nutritional status (e.g., normal, stunted, severely stunted, or tall). The prediction results are serialized to JSON and stored on IPFS to generate a CID, which is then recorded in the blockchain ledger to ensure immutability, auditability, and independent third-party verification. Meanwhile, for educational questions, the chatbot forwards user input to GPT-3.5 Turbo, which generates contextual, medical, and referenced answers. In the end, the system sends the results of the nutritional status classification back to the user via Telegram, along with the storage link and an educational response, thus forming a smart cycle of classification, safe storage, and user feedback.

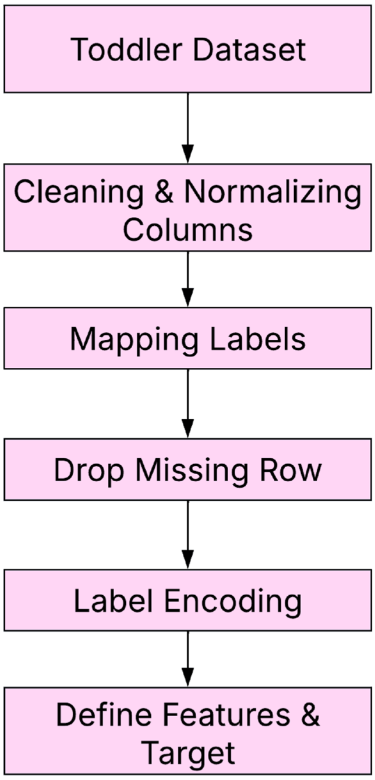
To support free-text classification, we developed a deterministic regular-expression-based local input handler. The pipeline includes the following: (i) structured pattern detection to extract three target entities (age, gender, and height); (ii) a bilingual Indonesian–English fallback parser for natural phrases that recognize integers/decimals (e.g., 2.5 years), abbreviations (month/year), number words (one–twelve), gender synonyms, and units of centimeter (cm) with comma/period separators; (iii) normalization and validation, i.e., age is converted to months and rounded, gender is mapped to L/P and binary encoded, height is standardized to cm, and validation is only at the age of 0–60 months; (iv) directional clarification in the event of a missing entity;

and (v) mapping to feature vectors and inference with trained random forest models. This design enables end-to-end reception of private, reproducible natural languages.

3.3. Dataset preprocessing

The data preprocessing process was rigorously implemented to produce high-quality, consistent, and machine-learning-ready data. First, we loaded the toddler nutritional status data. Categorical values in the "Gender" column were standardized by transforming to lowercase. The column "Nutrition_Status" was cleaned by converting to a string, removing whitespace, and converting all letters to lowercase. To improve model interpretability, we used a predefined mapping dictionary to convert nutritional status labels into normalized categories (normal, stunted, severely stunted, and tall). The rows with missing values in the columns to be joined on were then removed to maintain data integrity. The categorical features "Gender" and "Nutrition_Status" were subsequently labeled and encoded as numerical values. Finally, the data were divided into independent variables (age, gender, and height) and the dependent variable (nutritional status) to build models in the following stages. An overview of the entire preprocessing steps is shown in Figure 3.

Figure 3
Dataset preprocessing pipeline for toddler nutritional status classification



3.4. Ensemble model evaluation using cross-validation

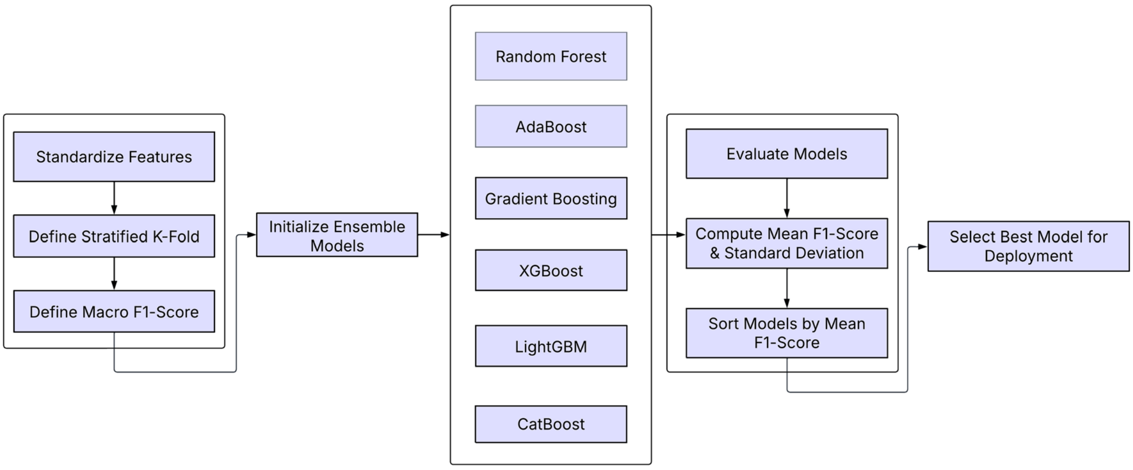
Figure 4 illustrates the process of feature standardization, stratified k-fold validation, F1-score computation, and ensemble model selection. To validate the models and determine the best ensemble algorithm for classifying toddler nutritional status, this study employed a stratified five-fold cross-validation. This procedure preserved the class distribution in the initial structure for all folds, yielding robust performance estimates. The entire feature set was standardized using StandardScaler before evaluation, thereby improving model performance and comparability. Six ensemble learning models were evaluated: random forest, AdaBoost, gradient boosting, XGBoost, LightGBM, and CatBoost. All models were also instantiated with 100 estimators and using a constant random state to achieve reproducibility. In this study, we evaluated our model's performance using the macro-averaged F1-score, which is suitable for a multiclass classification problem with potential class imbalance.

The evaluation process used the cross_val_score function, which averaged performance across folds to calculate the mean F1-score and the standard deviation of each model. Models were ordered by their mean F1-scores, and the best classification model for deployment in the nutritional status classification system was then determined.

3.5. Random forest model training and evaluation

The training and testing stages provide a key systematic framework for building and testing a supervised machine learning model, including ensemble learning, in a structured and reproducible manner. Usually, a dataset is split into training and test sets, with 80% allocated to training and 20% to testing. This ensures that the testing set remains invisible during model development, allowing for an unbiased estimation of model performance. During the training phase, the model receives the training subset and learns the hidden patterns and correlations between the features and the target labels. This procedure constitutes a suitable tuning

Figure 4
Cross-validation workflow for ensemble model evaluation and selection



of the secret parameters for minimizing prediction errors. Evaluation is subsequently performed on the held-out testing subset to assess generalization to new data. This step is crucial for identifying possible issues, such as overfitting or underfitting. To measure classification performance, F1-macro, precision, recall, ROC AUC macro, and accuracy are used. These metrics provide a comprehensive reflection of the various target classes, enabling the model to perform well across multiple evaluation dimensions. Figure 5 illustrates the complete model development process, including dataset splitting, training the random forest classifier, testing the trained model, generating performance metrics, and evaluating overall model performance. This model is used for classifying toddlers' nutritional status by users.

Figure 5
Random forest model training and evaluation workflow

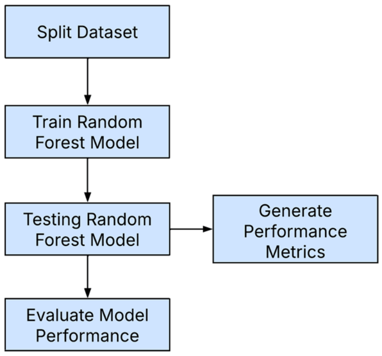
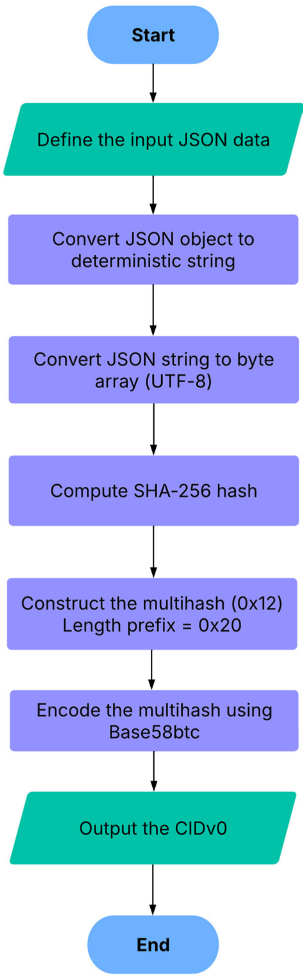


Figure 6
CID hashing workflow in IPFS using SHA-256 and Base58 encoding



3.6. IPFS and blockchain for decentralized storage

IPFS is a stack of protocols based on modules that focus on content addressing and data transfer. It uses CIDs to locate and access content rather than its physical location. This paper investigates the underlying principles of content addressing in IPFS through the lens of secure data referencing via its CIDs. The central mechanism of this system is a hash function, which plays a vital role in maintaining data integrity and security in blockchain applications.

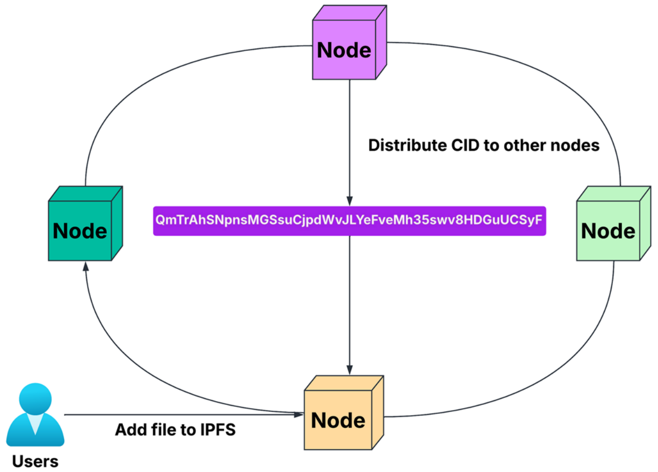
In Figure 6, digests produce unique cryptographic signatures that are difficult to tamper with and highly traceable. In doing so, we leverage the SHA-256 algorithm (derived from the multihash-256 protocol) to derive a fixed-size, tamper-resistant digital hash of the data that uniquely identifies each dataset—a crucial requirement for ensuring the integrity of sensitive data (e.g., child nutritional records)—and to compare these hashes among nodes. The resulting hashes are then converted to a more readable format using Base58 encoding, which reduces error-prone data processing and transmission while improving throughput and reliability.

Algorithm GenerateCIDv0FromJSON
Input: JSON object with fields (e.g., age, gender, height, nutritional status)
Output: CIDv0 string encoded in Base58btc format
Step 1: **Define the input JSON data**
data ← {
”age_month": 13,
” gender": "P",
”height_cm": 84.0,
"status":” tall"
}
Step 2: Convert the JSON object to a deterministic string format
json_string ← SerializeJSON(data, sort_keys=True, separators=(',', ':'))
Step 3: Convert the JSON string to a byte array using UTF-8 encoding
json_bytes ← ConvertToBytes(json_string, encoding="UTF-8")
Step 4: Compute the SHA-256 hash of the byte array
hash_digest ← SHA256(json_bytes)
Step 5: Construct the multihash format
sha256_code ← Byte(0x12) // SHA-256 multihash code
length_code ← Byte(0x20) // Length of SHA-256 hash = 32 bytes
multihash ← Concatenate (sha256_code, length_code, hash_digest)
Step 6: Encode the multihash using Base58btc
cid_v0 ← Base58Encode(multihash)
Step 7: Output the final CIDv0
Print ("CID v0 (base58btc):", cid_v0)
End Algorithm

The process shown in Figure 6 begins by defining a structured JSON input, which is converted into a deterministic string and subsequently encoded into a UTF-8 byte array. A SHA-256 hash is computed from the byte array, followed by the construction of a multihash using the standard prefix (0 × 12) and length indicator (0 × 20). This multihash is then Base58btc-encoded to generate the final CIDv0, which uniquely identifies the content in the IPFS network.

Consistent with the system's interest in data transparency and integrity, Figure 7 illustrates the decentralized storage system (IPFS), which supports the architecture's secure handling of sensitive health data. The user first uploads classification results (as JSON objects) to a local node with IPFS integration. Then, each file is hashed with SHA-256, yielding a unique CID that serves as an immutable reference to the file based on its content. This CID not only secures the immutability and verifiability of stored data, but it also provides a tamper-evident digital fingerprint. The CID, along with its file, resides locally and is distributed across several IPFS nodes for redundancy, availability, and protection against a single point of failure. When another node later retrieves the file, it uses the CID to fetch it, and any unauthorized modification would be detected because the identifier does not match. In this decentralized, content-addressed paradigm, AI-classified nutritional records can be securely, efficiently, transparently, and scalably stored. The model is based on advertisements from parties interested in our users' anonymous dietary data. Together, they make the architecture suitable for credible and auditable health data management in real-time childhood nutrition surveillance.

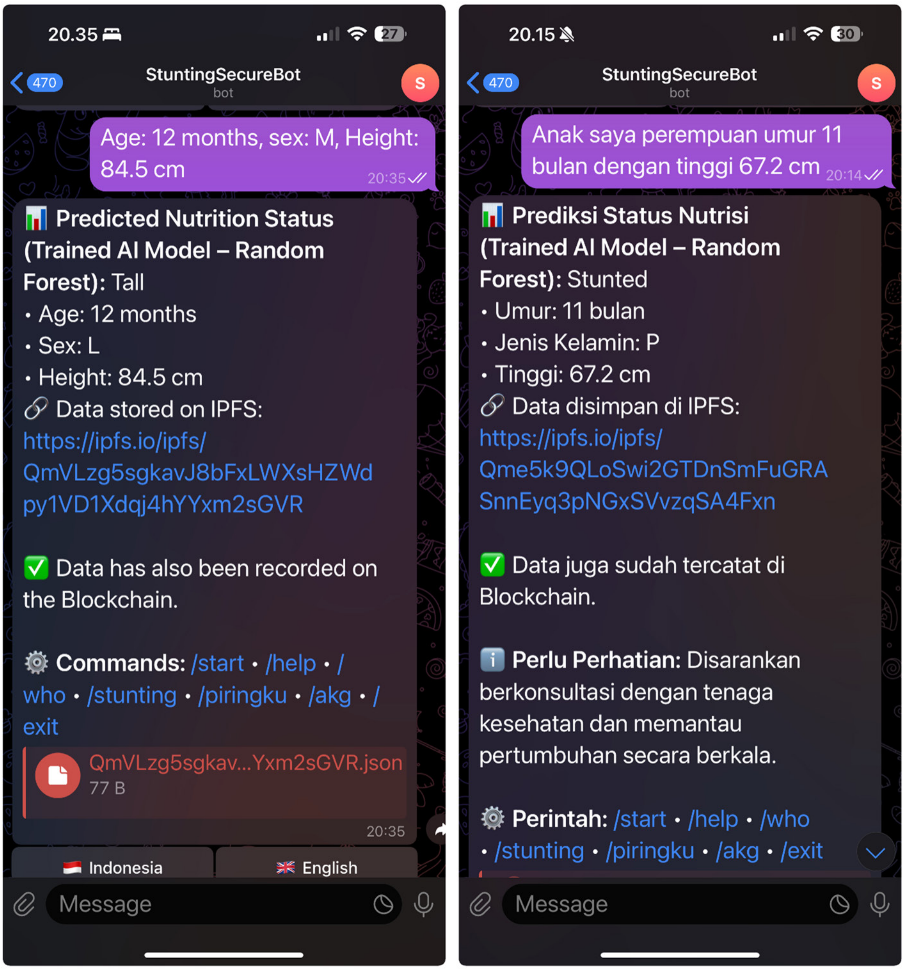
Figure 7
Decentralized storage workflow in IPFS using CID distribution across nodes



4. Experimental Results

The experimental results and a discussion on the performance of the proposed method and learners for the accurate classification of child nutritional status are presented in this section. The performance analysis highlights the usefulness of advanced ensemble techniques, particularly random forest, which enables robust performance across various dietary categories. The performance is evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and a confusion matrix, on test samples to assess the model's classification performance on unseen data. Aside from algorithm evaluation, it also incorporates decentralized technologies to ensure data integrity and traceability. One of the key innovations of this system is the introduction of an AI

Figure 8
Chatbot outputs for toddler nutritional status classification with secure storage via IPFS and blockchain



chatbot in Telegram, serving as an end-user support tool for real-time classification and health education on stunting. The user interacts with the chatbot by entering inputs (e.g., age, gender, and height), which are then passed to the trained model for nutritional status classification. The final output is presented on a messaging platform. The IPFS is used to store classification results in a distributed manner, facilitating data availability and preventing single-point failure. Simultaneously, blockchain technology is applied to digitally register the nutritional status classification results, allowing the nutritional status data to be tracked securely, tamper-proof, and auditable. These features collectively provide a robust and secure system architecture for intelligent health data management in the monitoring of early childhood nutrition.

4.1. Chatbot testing

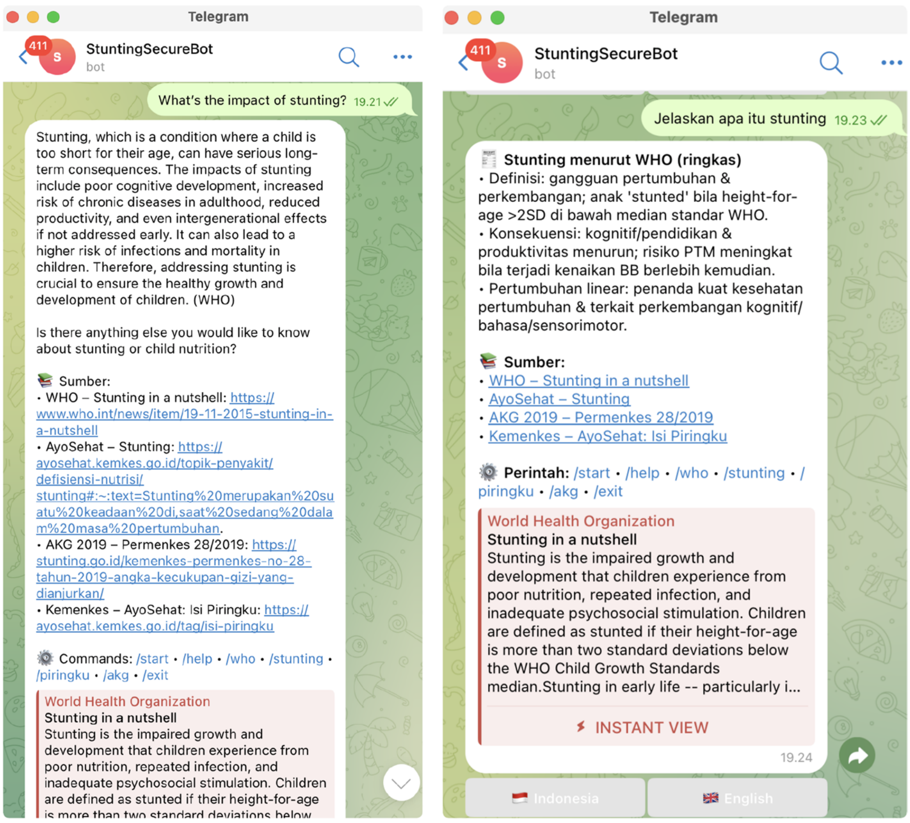
The outputs of the chatbot testing illustrated in Figure 8 show that teaching an intelligent and bilingual AI-based chatbot to perform two main functions, namely, (i) understanding questions regarding stunting in toddlers' demography and (ii) categorizing nutritional status according to personal data (age, sex, and height), was successfully processed. In the second interaction, the chatbot can accurately answer a natural-language question, such as "What is the stunting impact?," by providing comprehensive information on the subject. Thus, it serves its educational purpose with GPT-3.5 Turbo. The second interaction involves the chatbot receiving structured nutrition data. The chatbot then classifies the data using an ensemble learning model and responds to the user with the classification (e.g., "severely stunted" or "stunted") and a link to the data, securely stored via IPFS. It also verifies that the classification output has been written permanently to the blockchain. These findings demonstrate that the chatbot can provide real-time, interactive, and explainable health support, ensuring the interpretability and transparency of the classification results through decentralized storage and auditability.

In addition to its technical function, this system has a significant social and ethical role. Through AI, blockchain, and explainable mechanisms, parents and caregivers can be empowered to become active participants in tracking toddlers' nutritional status, even in areas with limited access to healthcare. This empowerment not only enhances caregiver awareness and decision-making but also fosters community-based nutrition monitoring by creating a collective responsibility for child growth and health. This approach reflects a commitment to equity and inclusivity in health technology design, ensuring that the benefits of AI-based solutions are fairly distributed to underserved and vulnerable populations [41].

In Figures 8 and 9, the chatbot's output demonstrates its significant potential to support early identification of stunting and classification of toddlers' nutritional status. In line with this, the research reported by Agarwal et al. [42] also shows that integrating a retrieval-augmented generation (RAG)-based LLM into multimodal medical chatbots effectively reduces hallucinations and increases the relevance of the answers. However, the study also highlighted several limitations, including fluctuations in responses to comparable questions, reliance on the adequacy of the underlying knowledge base, and insufficient capabilities in medical image interpretation. To address this gap, our research added safety controls.

Our proposed chatbot system is equipped with several safety control mechanisms to ensure a user experience and safety aspect. One of the important features is the implementation of nutritional safety alerts that will be activated when the classification results show a high-risk condition, such as severely stunted, so that parents or caregivers are immediately directed to seek medical consultation. In addition, a response filtering mechanism was implemented, supported by an adaptive dialog prompt, to ensure that the chatbot's answers remained

Figure 9
Chatbot outputs for stunting education in a bilingual context



limited to the domain of stunting education and nutritional status classification for toddlers. At the same time, questions outside the scope were automatically replaced with safer fallback responses. The system's resilience to misinformation is strengthened by grounding itself in trusted sources, such as the 2019 AKG and WHO guidelines, and by limiting the domain of answers and validating inputs to prevent misleading outputs. The combination of these mechanisms not only improves technical accuracy but also strengthens the aspects of reliability, security, and transparency, making chatbots better prepared for implementation in real-world health practices, especially as a trusted means of education and classification of the nutritional status of toddlers.

4.2. Cross-validation of the ensemble model

The ensemble model evaluation based on the cross-validation results shown in Figure 10 and Table 3 reveals that different classifiers exhibit noticeable performance differences in macro-averaged F1-scores and their corresponding standard deviations. With a mean F1-score and only slight variation, the random forest model achieved the highest predictive accuracy among all classes in the nutritional status classification task. LightGBM and XGBoost were right behind and demonstrated good performance with low standard deviations, further supporting their robustness and stability. We observed that CatBoost achieved a comparable mean F1-score, while gradient boosting slightly underperformed, indicating lower generalization. In addition, AdaBoost showed significantly worse performance in both the average F1-score and variance, reflecting sporadic and less appropriate classification for the task. In summary, these observations confirm the overall advantages of random forest in terms of providing high accuracy and reliability, indicating that random forest is the most favorable candidate for building a secure, decentralized AI system to predict toddler nutritional status.

Figure 10
Mean F1-score comparison of ensemble models

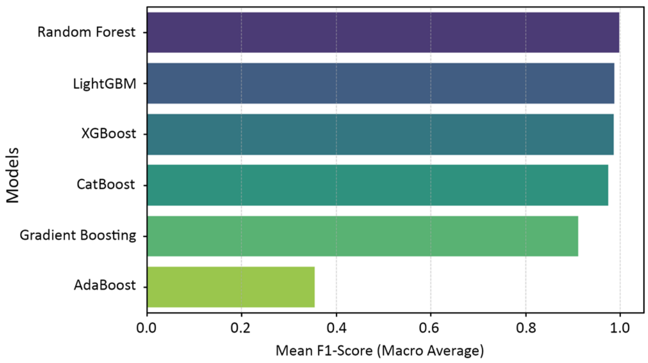


Table 3
The comparison result of cross-validation

No.	Model	Mean F1-score	Std Dev
1	Random forest	0.9987	0.0002
2	LightGBM	0.9872	0.0007
3	XGBoost	0.9871	0.0009
4	CatBoost	0.9745	0.0009
5	Gradient boosting	0.9119	0.0040
6	AdaBoost	0.3547	0.0274

4.3. Model performance evaluation

The random forest-based nutritional status classification model is tested on the 20% held-out test set and demonstrates satisfactory performance on all key measures (Figure 11). The F1-macro score of 0.99, the precision of 0.99, the recall of 0.99, the ROC AUC of 1.00, and the accuracy of 0.99 of the model demonstrated the very robust and balanced classification effectiveness of the target classes. The confusion matrix also reflects the model's ability to differentiate between the nutritional status categories of normal, severely stunted, stunted, and tall, with almost minimal misclassification. For example, among 13,548 normal cases, only 3 cases were misclassified, while the classification of 3,972 severely stunted and 3,908 tall cases was almost perfect. The best area under the ROC curve (ROC_AUC_multi = 1.00) indicates that the model's discriminating ability is excellent. These findings collectively demonstrate that the model can effectively generalize to unseen data and is thus suitable for reliable deployment in nutritional status classification tasks.

In this study, we provide a detailed methodological explanation of the validation procedure to alleviate concerns regarding overfitting and data leakage. The ensemble model's performance was evaluated using stratified five-fold cross-validation to maintain class distributions across folds and prevent data leakage between the training and test partitions. In addition to a 20% hold-out test set, the model's performance was further confirmed on external datasets, yielding strong and stable results, as illustrated in Figure 12 (F1-macro of 0.97, precision of 0.97,

Figure 11
Confusion matrix of the random forest model for nutritional status classification (test set 20%)

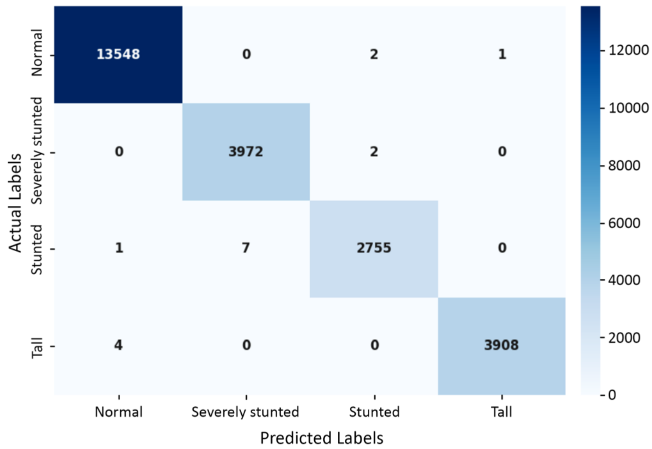
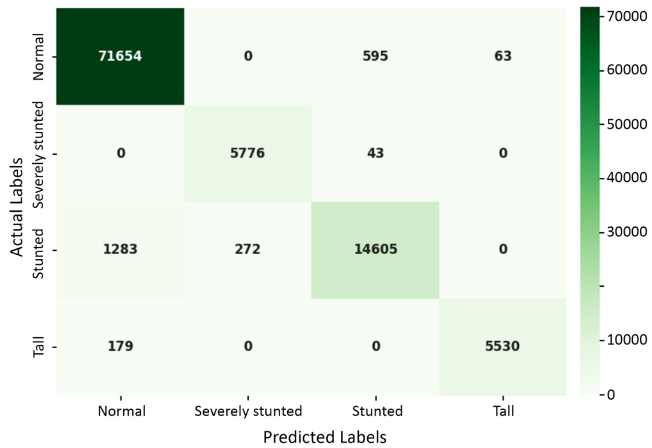


Figure 12
Confusion matrix of the random forest model for the new dataset



recall of 0.96, ROC AUC of 0.98, and accuracy of 0.97). These findings suggest that the model's predictive performance is not confined to the training distribution and generalizes well to other data sources. This out-of-sample validation reinforces the robustness, transparency, and generalization capacity of the proposed system while minimizing the risk of overfitting.

4.4. IPFS and blockchain transaction evaluation

Figure 13 shows a graph of the frequency of CID transactions over time, with block numbers from the blockchain. A point is shown for each transaction that is successfully recorded and should have an increasing block allocation, indicating dependable and persistent data recording. Specifically, the block number increased smoothly from block 29 to block 46 over a 15-min survey period (from 07:45 to 08:00). Because the pattern is linear, the transaction throughput is relatively constant, and no performance degradation (i.e., delay or queuing) was observed during the testing period. This timeline presentation confirms the blockchain's operational stability and verifies its feasibility as a decentralized, traceable platform for storing AI-classified health data.

The trend in Figure 14 regarding gas prices shows a precise figure illustrating the dynamics of efficiency within the network during the CID transaction. The curve shows a noticeable, regular decrease in gas prices with increasing block numbers, indicating that the cost of smart contract execution transactions decreases over time. First, the gas price is initially set at approximately 4.2×10^7 Wei at block 27 and drops to less than 0.27×10^7 Wei at block 47. The average rate of decrease can be quantitatively estimated to be about the same after the block range. Then, the transaction cost efficiency would be much lower than before. Small oscillations (e.g., between blocks 44 and 46) demonstrate virtually no gas price variations $< 0.5 \times 10^7$ Wei, which indicates a very stable price profile. This downward trend indicates a decrease in network congestion or an improvement in transaction processing, both of which are positive for scalability. This trend is particularly relevant for applications that regularly store data, such as AI-processed health data, as it offers a cheaper, more sustainable, and scalable environment for the chain. By lowering the gas price threshold per block, the system enables low-cost CID storage, making it suitable for long-term deployment in resource-limited, privacy-conscious health informatics settings.

Figure 13
Timeline of CID transactions in the blockchain

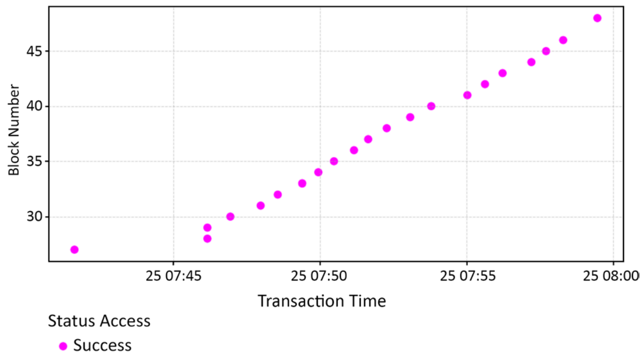
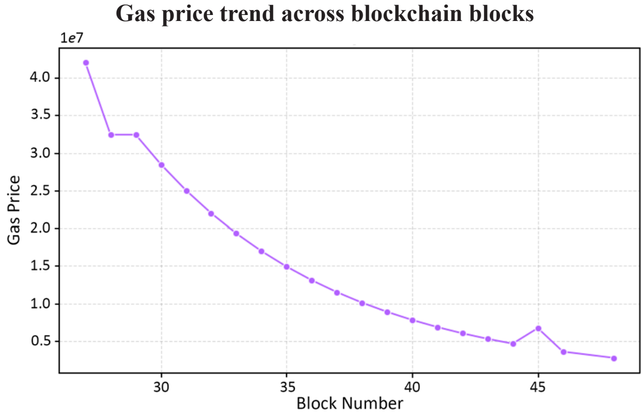


Figure 14
Gas price trend across blockchain blocks



The proposed system not only demonstrates good technical performance and blockchain stability but also emphasizes the integration of security mechanisms to protect user data. The study reported by Selvi et al. [43] emphasizes that user data protection in web chatbot systems requires a layered approach, including secure authentication through password storage in hash form using strong algorithms and the implementation of multifactor authentication, comprehensive encryption using the Advanced Encryption Standard (AES) for stored data and Transport Layer Security/Secure Sockets Layer (TLS/SSL) for transmitted data, and the implementation of Role-Based Access Control (RBAC) to limit access rights according to user roles.

In this study, the proposed system ensures data privacy through an integrated framework comprising authentication, encryption, and access control. User authentication is handled through a verified Telegram account, allowing only parents and licensed healthcare workers to access the service. Data confidentiality and integrity are maintained by hashing the results of nutritional status classification using the SHA-256 algorithm, storing the results in JSON format on IPFS, and permanently recording CIDs on the Ethereum blockchain, enabling immediate detection of any unauthorized modifications. Access control is implemented through smart contracts that grant read and write permissions based on user roles, adhering to the principle of minimum access rights. This multilayered approach ensures that only authorized users can interact with the chatbot, that sensitive toddler health data remain protected, and that all transactions can be audited through the blockchain's immutability.

5. Conclusion

This research presents a successful result, demonstrating that a hybrid AI chatbot approach can serve as an alternative for classifying toddlers' nutritional status and providing educational counseling in a decentralized, privacy-secure manner. Ensemble learning integrated into GPT-3.5 Turbo, leveraging the IPFS blockchain, ensures robust classification, real-time data interaction, and tamper-proof storage while maintaining transparency and interpretability.

There are several limitations in this study. The dataset used is synthetic and consists only of age, gender, and height features. Therefore, its generalizability to diverse real-world populations is limited. The system also requires a persistent internet connection, which may discourage its use in regions with poor connectivity. To overcome these challenges, we are planning to integrate clinical and community datasets with additional predictors (e.g., dietary intake, medical history, and socioeconomic status), deploy hybrid/partially offline models for underserved populations, and develop innovative data privacy methods, such as federated learning. Furthermore, future work will incorporate more complex models once multimodal datasets (including clinical, image-based, and socioeconomic data) are integrated, thereby enabling broader benchmarking and improved generalizability for real-world healthcare applications. In addition, the study did not include longitudinal field validation to evaluate real adoption, changes in caregiver behavior, and post-implementation impacts, which we identified as essential directions for future research.

While the current system has ensured the authenticity and traceability of data through IPFS and blockchain, comprehensive privacy protection still requires integrating advanced authentication, encryption, and access controls, which we identify as a future development direction.

Finally, the proposed system shows technical feasibility and social relevance, paving the way for scalable, trustworthy, and community-centered health data applications. Longer-term studies and real-world pilot studies will be needed to validate usability, collect user feedback, and measure the impact on caregiver practices, child nutritional surveillance, and large-scale efforts to reduce stunting.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/rendiputra/stunting-balita-detection-121k-rows and https://www.kaggle.com/datasets/jabirmuktabir/stunting-wasting-dataset.

Author Contribution Statement

Wa Ode Siti Nur Alam: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Riri Fitri Sari:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

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