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MultiModal Explainable AI and Blockchain Integration for Automated Halal Verification of Cosmetic Products

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ABSTRACT: This research develops a framework that integrates blockchain technology and MXAI (Multimodal Explainable Artificial Intelligence) to automate the authentication and verification of halal cosmetic products. Two data sources were used: text extracted by OCR (Optical Character Recognition) and text manually input from cosmetic labels. After the pre-processing stage, the text data are analyzed using zero-shot classification to determine the inspection results, namely halal, haram, or syubhat. The inspection is conducted using MXAI, with decisions based on confidence scores and SHAP values. The inspection results are converted into digital reports as SHA-256 hashes and stored as Merkle roots on the blockchain, allowing users to download certificates as QR codes. The halal status experiment on the cosmetics dataset achieved an accuracy of 94.5% for classification, with a 3.3% improvement over baseline models, evaluated using stratified 5-fold cross-validation. This system enhances transparency, accountability, and public trust in automated halal certification. The contribution of this research is the integration of MXAI and blockchain technology into a single intelligent halal verification system, which can be extended to other supply chain sectors.

ABSTRAK: Kajian ini menggabungkan teknologi rantaian blok dan MXAI (Kecerdasan Buatan Penjelasan Multimodal) bagi automasi dan jaminan pengesahan produk kosmetik halal. Dua sumber data digunakan: teks yang diekstrak oleh OCR (Pengesahan Optik Karakter) dan teks yang dimasukkan secara manual daripada label kosmetik. Selepas peringkat pra-pemprosesan, data teks dianalisis menggunakan klasifikasi sifar-tembakan bagi menentukan keputusan pemeriksaan, iaitu halal, haram, atau syubhat. Pemeriksaan dijalankan menggunakan MXAI, dengan keputusan berdasarkan skor keyakinan dan nilai SHAP. Keputusan pemeriksaan ditukar menjadi laporan digital dalam bentuk hash SHA-256 dan disimpan sebagai punca Merkle pada rantaian blok, membolehkan pengguna memuat turun sijil dalam bentuk kod QR. Eksperimen status halal pada set data kosmetik menunjukkan ketepatan 94.5% untuk prestasi pengelasan, dengan peningkatan 3.3% berbanding model asas, dinilai menggunakan pengesahan silang 5-lipatan berstrata. Sistem ini meningkatkan ketelusan, akauntabiliti, dan kepercayaan awam dalam pensijilan halal automatik. Sumbangan penyelidikan ini ialah melalui integrasi MXAI dan teknologi rantaian blok dalam satu sistem pengesahan halal pintar tunggal, yang boleh diperluas kepada sektor rantaian bekalan lain.

KEYWORDS: *Halal Verification System, Blockchain, MXAI (Multimodal Explainable Artificial Intelligence), Multimodal Learning, OCR (Optical Character Recognition).*

1. INTRODUCTION

Artificial Intelligence (AI) has become increasingly integrated into modern society and has become an important component of it since the Industrial Revolution 4.0. AI has been used in various sectors. The accuracy of AI-driven decision-making and automation makes it an irreplaceable tool. The use of AI has had an impact on various industrial sectors, including the halal cosmetics industry, due to consumer demand for high-quality halal products[1].

Research on the halal cosmetics industry remains limited, particularly regarding the use of artificial intelligence (AI). Research in this field still faces several challenges, such as raw material analysis, halal certification processes, and marketing strategies for both Muslim and non-Muslim markets. The development of AI has had a significant impact on various sectors, including the optimization of halal product development and certification procedures [2].

Artificial Intelligence (AI) capabilities are far superior to traditional decision support systems in processing large, complex datasets, especially in making more accurate and efficient decisions. The integration of real-time decision-making with intelligent automation is replacing traditional decision support systems [3]. The ability to learn from new data and adapt to emerging challenges is one of AI's remarkable capabilities. This makes it particularly important for industries that require quick, accurate, and timely decisions.

At the same time, blockchain technology is reshaping various sectors such as healthcare, supply chain management, and other fields by enhancing data security and maintaining integrity through permanent audit trails [4]. In the halal supply chain, blockchain ensures traceability and transparency, preventing manipulation and maintaining the authenticity of halal products [5], [6]. The decentralization of blockchain makes it crucial for securing the halal certification process and fostering trust within the industry.

The integration of blockchain and AI has proven transformative across various industrial sectors. In many higher education institutions, this integration enables efficient certificate management by automating verification through smart contracts, thereby enhancing security and transparency [7], [8]. This synergy offers innovative applications in identity verification, authenticity detection, and contract management [9], [10]. Similarly, the industry benefits from an efficient and more reliable certification system that utilizes both technologies [11], [12].

The halal certification process remains inefficient despite being essential for Muslims. The certification process is time-consuming, costly, and prone to fraud and mislabeling. Regulatory challenges and inconsistencies complicate global halal standards [13], [14] Thus, there is an urgent need to digitalize the certification process to ensure data authenticity and efficiency.

Although AI and blockchain have been applied in the food industry and supply chain management [15],[4]. There is still no integrated framework that combines the two, so there is a need to integrate blockchain with Explainable Artificial Intelligence (XAI), especially in the cosmetics industry. In the cosmetics industry, challenges such as ingredient analysis, system transparency, and certification compliance remain unaddressed. This research aims to develop an integrated framework that combines XAI and blockchain to automate and improve the halal verification process for cosmetics.

This research proposes a new approach that combines Multimodal Explainable AI (MXAI) with blockchain technology to verify the halal status of cosmetic products. The system will analyze product label images, ingredient texts, and supporting documents. It will offer explainable interpretations of halal classification. With the potential of AI and blockchain, this framework will provide a more efficient, transparent, and secure halal certification process. It will contribute to the modernization of halal governance and meet the demand for trustworthy halal products.

2. METHODOLOGY

2.1. Research Design

This research uses a prototype system development design based on MXAI (Multimodal Explainable Artificial Intelligence) and Blockchain to verify the halal status of cosmetic products. The data used comes from two sources: packaging label images and ingredient composition texts. The MXAI method was chosen because it allows the system to understand visual and textual contexts simultaneously, while blockchain technology ensures the security, transparency, and traceability of verification results. The research stages included: 1. collection of cosmetic label datasets, 2. multimodal data pre-processing, 3. MXAI model training and testing, 4. blockchain integration for digital recording and auditing, and 5. system testing through a Gradio-based user interface (UI). The overall architecture of the proposal, MXAI and blockchain-based halal verification framework, is illustrated in Fig. 1.

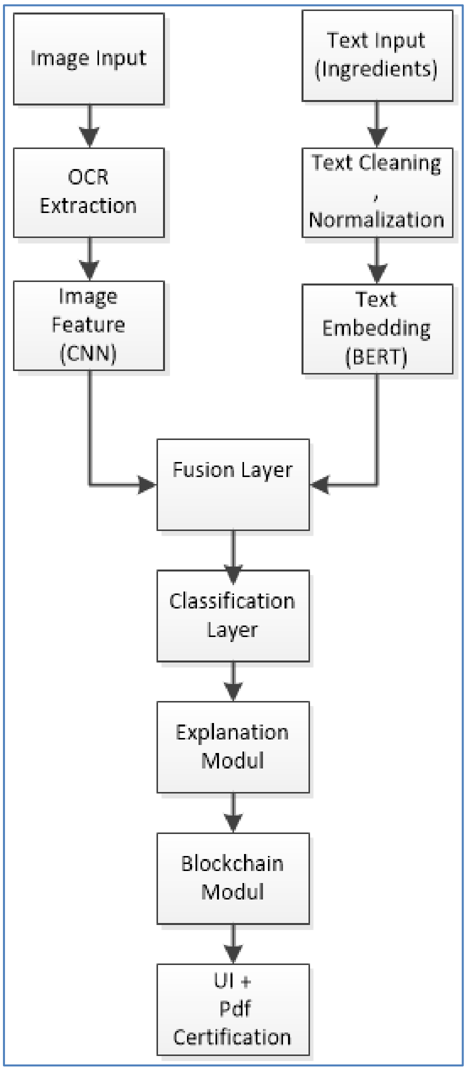

Figure 1. Halal verification framework for cosmetic products

2.2. Data Source

The data used consisted of two main sources, textual data and visual data:

1) *Textual Data*: data in the form of a list of cosmetic ingredients that is manually entered by users into the system. The data format is text that lists product ingredients, such as water, tocopherol, and glycerine. This data is used as a reference for the validation and classification process of the halal status of ingredients.
2) *Data Visualization*: data in the form of cosmetic packaging labels containing ingredient composition information. The images are processed with Optical Character Recognition (OCR), and the text is extracted using the *pytesseract* library. The extracted text is then compared and fused with manually inputted textual data to produce a combined representation.

Both types of data are processed in parallel using multimodal learning. Information from text and images is combined using attention-based embedding fusion techniques to improve the accuracy of classifying a cosmetic product as halal, dubious, or haram.

2.3. Data Preprocessing and Workflow Procedure

The data processing stages in this study were carried out in stages. Data obtained from text and OCR was processed by the MXAI model. The data processing steps included:

2.3.1. Manual data input and OCR Labeling

The text of the cosmetic ingredient composition is entered into the system, or the label image is uploaded. The system will extract the text from the uploaded image data using Optical Character Recognition (OCR) with pytesseract.

2.3.2. Text Cleaning and Normalization

The text results from OCR and manual input are then cleaned of noise (punctuation marks, capital letters, and ASCII characters) using regular expressions. All text is converted to lowercase to maintain consistency.

2.3.3. Stopword Removal and Tokenization

Words that do not have significant meaning (not, in, to, from, and others) are removed using Indonesian and English stopword lists. Tokenization is the process of converting words into their root forms.

2.3.4. Word Embedding

The cleaned text is converted into a numerical representation using the pre-trained multilingual BERT-base language model, and then contextual embeddings are generated for each word in the material.

2.3.5. Feature Extraction

For image data, product label images are resized to 224×224 pixels, normalized, and then fed into a Convolutional Neural Network (CNN).

2.3.6. Feature Fusion Layer

Representations of two data sets (text and image) are combined using a weighted fusion layer.

$$\mathbf{s} = \alpha \mathbf{s}_{text} + (1-\alpha)\mathbf{s}_{image}, \quad 0 \le \alpha \le 1 \tag{1}$$

where $\mathbf{s}_{text}$ is the class-score vector produced from the text encoder, $\mathbf{s}_{image}$ is the class-score vector produced from the image encoder, and α is the modality-weighting coefficient learned or tuned during training.

2.3.7. Classification and Explainability

The resulting combined score is sent to the classification layer, which produces the final label (halal, dubious, haram). The system activates the explainability module to highlight the words that most influence the model's decision.

2.3.8. Blockchain recording

The verification results, which include the halal status, document hash, and timestamp, are recorded in the blockchain ledger using the SHA-256 algorithm. Each block contains the following structure:

$$B_i = \{i, t_i, d_i, h_{i-1}, h_i\} \quad (2)$$

where i is the block index, t_i is the timestamp, d_i is the verification data, h_{i-1} is the previous block hash, and h_i is the current block hash.

2.4. MXAI Architecture

The MXAI (Multimodal Explainable AI) architecture has three main components: the text encoder, the image encoder, and the Fusion and Classification Layer. These three components work in an integrated manner to produce predictions of halal, dubious, or haram status based on multimodal analysis.

2.4.1. Text Encoder (BERT)

The text encoder uses Bidirectional Encoder Representations from Transformers (BERT) to capture semantic relationships among ingredient terms. Each cosmetic ingredient sequence is represented as:

$$T = \{t_1, t_2, t_3, \ldots, t_n\}$$

The contextual text representation is then obtained as:

$$\mathbf{h}_{text} = f_{BERT}(T) \quad (3)$$

where T denotes the tokenized ingredient sequence, t_i represents the i-th ingredient token, and $\mathbf{h}_{text}$ is the contextual vector representation of the cosmetic product ingredient text, e.g., the relationship between alcohol, glycerine, and collagen, for further analysis by the AI model.

2.4.2. Image Encoder (CNN)

This component extracts visual features from cosmetic product packaging labels. OCR processes images I are processed through a Convolutional Neural Network to extract visual semantic features

$$\mathbf{h}_{image} = f_{CNN}(I) \quad (4)$$

where I is the input product-label image and $\mathbf{h}_{image}$ is the visual feature representation extracted by the CNN.

2.4.3. Layer Fusion and Classification Features

After the representations of the text and image are obtained, they are combined using a weighted fusion layer with the formula:

$$\mathbf{s} = \alpha \mathbf{s}_{text} + (1-\alpha)\mathbf{s}_{image},\ 0 \leq \alpha \leq 1 \tag{5}$$

Where $\mathbf{s}$ is the fused class-probability vector, $\mathbf{s}_{text}$ is the probability score of text analysis results, $\mathbf{s}_{image}$ is the image analysis probability score, and α is the weight of the text modality contribution, adjusted during the training process to achieve optimal results

The final value $\mathbf{s}$ is used to determine the halal classification of products with decision functions:

$$\hat{y} = \arg\max_{c \in \mathcal{C}} \mathbf{s}_c \tag{6}$$

where $\mathcal{C} = \{halal, syubhat, haram\}$, $\mathbf{s}_c$ is the predicted score for the class c, and $\hat{y}$ is the final predicted halal-status label.

2.4.4. Loss Function

In addition, the model was trained using a combined loss function that optimized accuracy while maintaining consistency across modalities. The total loss function was defined as follows:

$$\mathcal{L}_{total} = \mathcal{L}_{CE} + \lambda \mathcal{L}_{InfoNCE} \tag{7}$$

$$\mathcal{L}_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{\mathcal{C}} y_{i,c}\log(\hat{p}_{i,c}) \tag{8}$$

$$\mathcal{L}_{InfoNCE} = -\log \frac{\exp\left(\frac{sim(\mathbf{h}_{text},\mathbf{h}_{image})}{\tau}\right)}{\sum_{j=1}^{N}\exp\left(\frac{sim(\mathbf{h}_{text},\mathbf{h}_{image,j})}{\tau}\right)} \tag{9}$$

where $\mathcal{L}_{CE}$ is the Cross-Entropy Loss for multi-class classification, $\mathcal{L}_{InfoNCE}$ is the contrastive alignment loss that ensures consistency between text and images, λ is the coefficient regulating the contribution between the two losses, and τ is the temperature parameter that controls the sharpness of similarity scores in the contrastive loss.

The methods ensure that the system is not only capable of recognizing halal status from textual and visual content but also has strong cross-modal alignment, resulting in more accurate and explainable decisions.

2.4.5. Blockchain Recording

For traceability, each verification record is stored in a Python-based blockchain. Each block structure is defined as described in Eq. (2). Then, the hash block i calculated using the SHA-256 algorithm:

$$h_i = SHA256(i \parallel t_i \parallel d_i \parallel h_{i-1}) \tag{10}$$

where $\parallel$ denotes concatenation.

2.4.6. Merkle Root Verification

To ensure data integrity, all transactions in a block are summarized using a Merkle tree, with the formula:

$$R = H\big(H(T_1 \parallel T_2) \parallel H(T_3 \parallel T_4)\big) \tag{11}$$

where R is the Merkle root, $H(\cdot)$ denotes the SHA-256 hash function, T_1, T_2, T_3, T_4 are transaction records, and $\parallel$ denotes concatenation.

2.5. Implementation Tool

The test environment and implementation tools used in this study are summarized in Table 1. All components were selected to ensure compatibility between AI, blockchain, and document module creation. This configuration is designed to support multimodal data processing, model deployment, and certificate creation within the verification integration framework.

Table 1. The test environment and implementation tools used in this study

Component	Technology/Tool
Programming Language	Python 3.10
AI Framework	PyTorch, Transformers
Supporting Libraries	Pytesseract, OpenCV, Gradio, qrcode, ReportLab, haslib
Blockchain Framework	Custom lightweight blockchain
Development Environment	Google Colab, Gradio
Certificate Format	PDF certificate with QR code generated using ReportLab and qrcode

The configuration of tools in Table 1 optimizes system performance during model training, blockchain verification, and certificate creation. The integration of Gradio and ReportLab enables interactive, transparent prototypes for halal product verification, while the use of Python-based blockchain-lightweight supports efficient ledger recording and data integrity validation.

2.6. Data Analysis Techniques

The data analysis stage was conducted to evaluate the performance of the MXAI and Blockchain verification system. Two types of analysis were used: (1) AI model performance and (2) Blockchain integrity.

2.6.1. AI Model Measurement

Classification accuracy using the standard formula is:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

The measurements are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), respectively. Precision and recall measurements are also provided, and the F1 score is calculated to assess class-balanced performance.

$$Precision = \frac{TP}{TP+FP}, Recall = \frac{TP}{TP+FN}, F_1 = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{13}$$

The consistency of explanations is measured using the metrics of fidelity and sparsity, defined as follows:

$$Fidelity = 1 - \frac{|f(x)-f(x_{\setminus S})|}{|f(x)|+\epsilon}, Sparsity = \frac{\|S\|_0}{\|x\|_0} \tag{14}$$

where $f(x)$ is the model output for the original input x, $x_{\setminus S}$ is the input after removing the important features identified by SHAP, S is the set of features selected by SHAP, $\|\cdot\|_0$ denotes the number of non-zero elements, and ϵ is a small constant used to avoid division by zero. High fidelity and low sparsity indicate that the explanation is faithful to the model decision while remaining concise.

2.6.2. Blockchain integrity.

Blockchain integrity was validated using hash consistency across linked data blocks, defined as:

$$H_i = SHA256(i \parallel t_i \parallel d_i \parallel H_{i-1}) \quad (15)$$

where i is the block index, t_i is the timestamp, d_i is the verification data, H_{i-1} is the hash of the previous block, and ∥ denotes concatenation.

The verification is successful when:

$$H_i^{computed} = H_i^{recorded} \quad (16)$$

This ensures that no unauthorized modification occurs in the current or previous linked blocks. Data analysis, therefore, supports accuracy from the AI perspective and immutability from the blockchain perspective.

2.7. Validation Procedure

To ensure system reliability, a two-stage validation process was conducted: internal and external validation.

2.7.1. Internal Validation

Internal validation assessed the accuracy of AI-based halal classification by comparing the system's predictions against expert-labeled ground-truth data. Internal validation accuracy (V_{int}) was calculated as:

$$V_{int} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}(\hat{y}_i = y_i) \quad (17)$$

where N is the total number of samples, $\hat{y}_i$ is the predicted label, $y_i$is the expert label, and $\mathbb{I}(\cdot)$ is an indicator function that returns 1 when the prediction matches the expert label and 0 otherwise.

A high V_{int} score indicates strong agreement between the AI model and expert assessment.

2.7.2. External Validation

External validation assessed the transparency and integrity of the blockchain-based certificate mechanism. Each verification record was traced via QR code scanning to ensure public access to verification data and via Merkle root verification to ensure transaction integrity within a block. The Merkle root was verified using the formulation defined earlier in Eq. (11). When the computed Merkle root matched the stored Merkle root, the certificate record was considered valid and tamper-evident.

3. RESULTS

3.1. Experimental Setup

The prototype was implemented in Google Colab using Python 3.10. The core modules used include pytesseract (for OCR), transformers (for text classification), *opencv* (for image pre-processing), *hashlib* (for SHA-256 hashing), gradio (for the user interface), as well as reportlab and qrcode for creating PDF certificates and QR codes. A total of 214 cosmetic products from local and imported brands were analyzed, consisting of 142 halal (H), 38 haram (R), and 34 syubhat (S). Each record includes:

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- Product label image (JPEG/PNG format, 300 dpi resolution)
- List of extracted ingredients (manual input).

An example of the OCR-based ingredient extraction process is illustrated in Fig. 2, while the manual ingredient input interface is shown in Fig. 3.

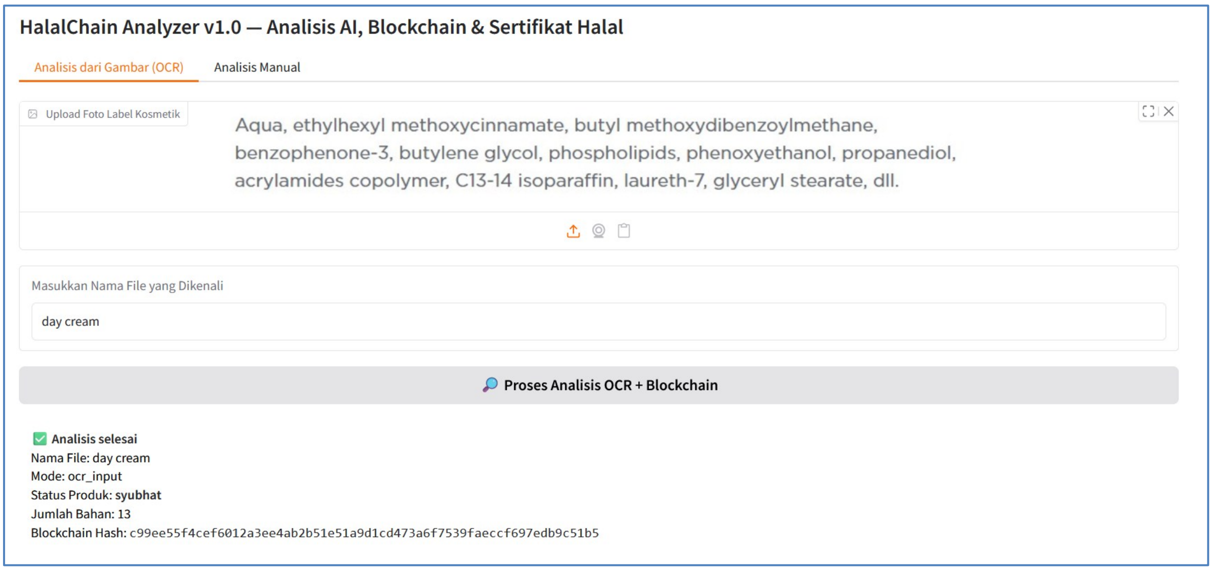


Figure 2. OCR Input

Ground-truth labels were established through expert review of ingredient lists, supported by authoritative halal ingredient databases and fiqh-based rulings on ingredients. Ingredients with ambiguous or disputed halal status were categorized as syubhat.

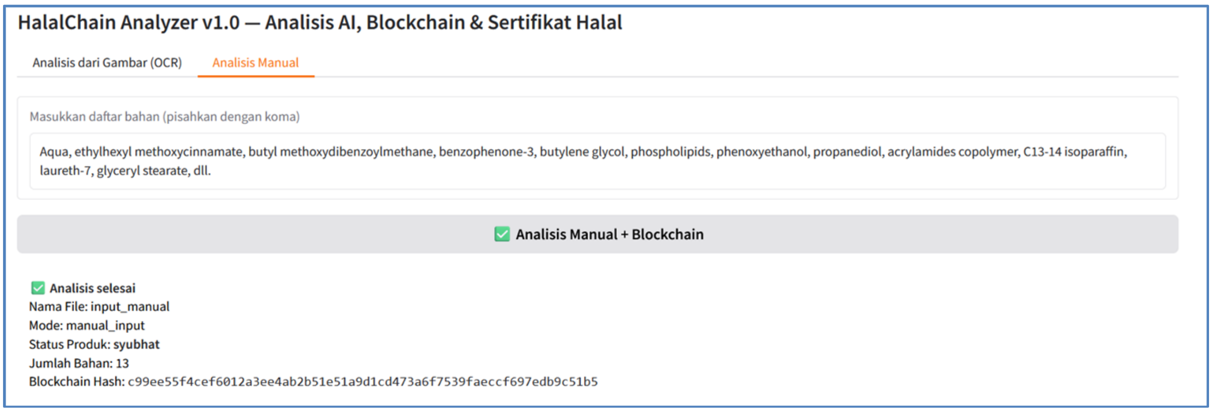
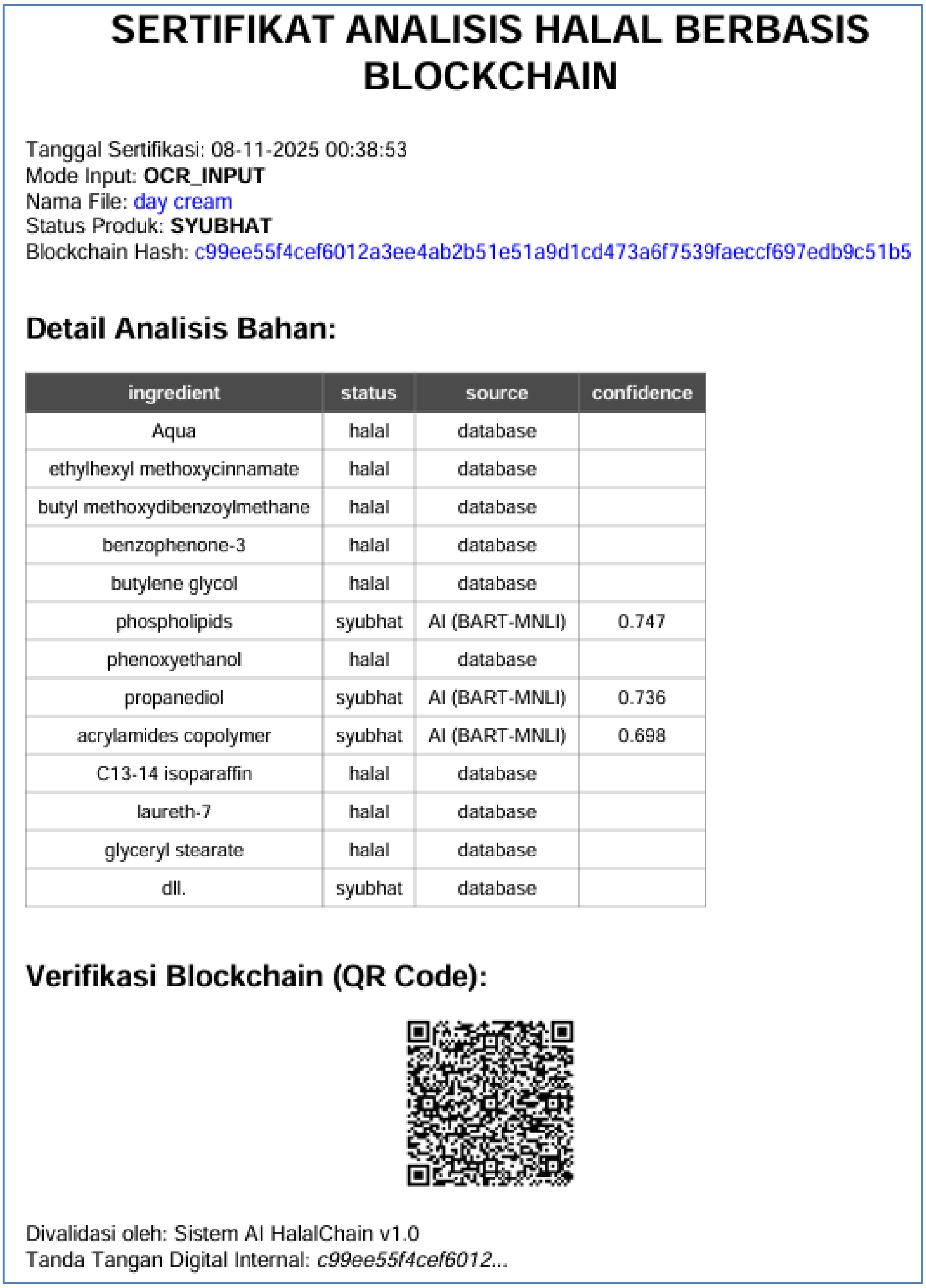


Figure 3. Manual Input

To evaluate the model, a 5-fold cross-validation technique was employed to ensure more consistent outcomes and preserve class balance across halal, haram, and syubhat. The dataset was split into training and testing portions for each validation stage, with no overlap. The average of all validation steps was used to record the final performance evaluator results.

The integrated OCR (Optical Character Recognition) pipeline achieves an average accuracy of 92.7% in recognizing text after several stages of pre-processing, including removing noise, identifying light and dark boundaries, and correcting letter shapes. Common OCR errors were observed under low lighting, densely packed or small fonts, and curved product surfaces. An example of the blockchain-based verification certificate generated by the system is shown in Fig. 4.


SERTIFIKAT ANALISIS HALAL BERBASIS BLOCKCHAIN

Tanggal Sertifikasi: 08-11-2025 00:38:53
Mode Input: **OCR_INPUT**
Nama File: day cream
Status Produk: **SYUBHAT**
Blockchain Hash: c99ee55f4cef6012a3ee4ab2b51e51a9d1cd473a6f7539faeccf697edb9c51b5

Detail Analisis Bahan:

ingredient	status	source	confidence
Aqua	halal	database	
ethylhexyl methoxycinnamate	halal	database	
butyl methoxydibenzoylmethane	halal	database	
benzophenone-3	halal	database	
butylene glycol	halal	database	
phospholipids	syubhat	AI (BART-MNLI)	0.747
phenoxyethanol	halal	database	
propanediol	syubhat	AI (BART-MNLI)	0.736
acrylamides copolymer	syubhat	AI (BART-MNLI)	0.698
C13-14 isoparaffin	halal	database	
laureth-7	halal	database	
glyceryl stearate	halal	database	
dll.	syubhat	database	

Verifikasi Blockchain (QR Code):

Divalidasi oleh: Sistem AI HalalChain v1.0
Tanda Tangan Digital Internal: *c99ee55f4cef6012...*

Figure 4. Certificate of Input OCR

3.2. Model Performance

The integrated Optical Character Recognition (OCR) pipeline achieved an average text-recognition accuracy of 92.7% after the pre-processing stage, which included noise removal, thresholding, and token normalization. Common recognition errors occurred due to low lighting, overly dense and small text, and curved product surfaces. The transformer-based text classification component achieved the performance results shown in Table 2. All reported metrics represent average performance across 5-fold cross-validation.

Table 2. Average Performance Across 5-Fold Cross-Validation of the Text-Based Halal Classification Model

Metric	Value
Precision	90.2%
Recall	88.7%
F1-score	89.3%
Accuracy	91.2%

The verification process focuses primarily on ingredient composition extracted from OCR and manually entered text, since ingredient information is more reliable for halal verification than visual halal labels alone. In the proposed MXAI architecture, the text-based BERT component and image-based CNN component were combined using the weighted fusion mechanism defined earlier in Eq. (5). The fusion weight was set to $\alpha = 0.65$, indicating that the text modality contributed 65% to the final prediction, while the image modality contributed 35%. The value of $\alpha = 0.65$ was selected via grid search over values from 0.10 to 0.90 in increments of 0.05, as it yielded the best validation accuracy and maintained consistent SHAP explanations across cross-validation tests.

The proposed multimodal fusion model achieved an overall accuracy of 94.5%, outperforming both single-modal baseline models. The comparative results, averaged across 5-fold cross-validation, are presented in Table 3.

Table 3. Average Performance Across 5-Fold Cross-Validation: Accuracy Comparison Between Baseline Models and the Proposed MXAI+Blockchain System

Model Type	Accuracy	Improvement
Text-Only (BERT)	91,2%	-
Image-only (CNN)	87.6%	-
Proposed Fusion MXAI+Blockchain	94.5%	+3.3, improvement over the best baseline

The results show that the proposed multimodal approach surpasses the strongest single-modal baseline, namely the text-only BERT model, confirming the effectiveness of integrating textual and visual information within an MXAI and blockchain-based verification framework.

3.3. Comparison With Previous Research

To evaluate the novelty and effectiveness of the proposed Multimodal Explainable AI (MXAI) and Blockchain framework, a comparative analysis was conducted against prior research on halal verification and tracking. The comparison results are summarized in Table 4, highlighting differences in data modalities, explainability, blockchain integration, and reported accuracy across existing approaches and the proposed system.

Table 4. Comparison of Relevant Halal Verification and Tracking Methods

Method	Data	Explainability	Blockchain	Accuracy
Deep Learning [16]	Image data	no	no	91,8%
Comparative analysis [17]	Text and Image	no	no	72,5%
Evaluation [18]	Text and Image	yes	no	84%
Proposed MXAI+Blockchain System	Text dan Image	yes	yes	94,5%

Previous methods that focused on visual tracking and recognition, this research proposes integrating MXAI with Blockchain to ensure transparency and verifiable integrity. As shown in Table 4, existing studies primarily focus on processing single- or multimodal data without integrating explainability and blockchain-based integrity mechanisms. It is acknowledged that accuracy comparisons across studies may be influenced by variation in datasets and class distributions, particularly by the incorporation of explainable AI and blockchain-supported traceability, rather than asserting absolute performance superiority.

3.4. Blockchain Validation Results

The halal verification results were stored in a lightweight blockchain ledger using the SHA-256 hashing algorithm. Each block follows the structure defined earlier in Eq. (10), while hash consistency was validated using the formulation in Eq. (16). A total of 50 data records were verified in the simulation, with no inconsistencies detected. This indicates that all tested records maintained hash consistency during validation.

The Merkle tree structure was used for batch validation, as defined earlier in Eq. (11). This enables efficient verification of certificate records without exposing sensitive product data. All verified certificates generated a QR code linked to the blockchain hash and product verification record.

4. DISCUSSION

The research successfully developed a system prototype for verifying halal cosmetic products that integrates blockchain technology and Multimodal Explainable Artificial Intelligence (MXAI) to improve accuracy, transparency, integrity, and traceability. This prototype uses two data module sources: text from product labels and visual labels from OCR to produce halal, haram, or syubhat status classifications, achieving an accuracy of 94.5%.

This approach, which combines textual and visual labels of cosmetic products, improves classification results. Meanwhile, SHAP provides an explanation of AI concepts. Blockchain integration ensures that verification results are accurate, publicly accessible, and immutable.

4.1. Computational Cost and Scalability Considerations

From a computational perspective, the proposed Multimodal Explainable AI (MXAI) System is designed to balance accuracy and efficiency. The use of a pre-trained multilingual BERT-base model introduces moderate training overhead but remains efficient during inference due to the relatively short length of ingredient lists, while the image-processing stage is limited to OCR-based text extraction using a lightweight CNN. The multimodal fusion relies on simple weighted score aggregation, resulting in minimal additional computational cost. Training and evaluation were conducted in a cloud-based environment, and deployment-time complexity remains practical for large-scale use. The system can be scaled through batching or containerized microservices to support high-throughput halal verification.

4.2. Blockchain Implementation and Real-World Deployment Considerations

The blockchain component is implemented as a Python-based lightweight blockchain to demonstrate feasibility, transparency, and data integrity in a controlled setting. Only essential information, including halal status, document hash, timestamp, and Merkle root, is recorded to minimize storage overhead and latency. For real-world deployment, the framework can be extended to permissioned or consortium blockchain platforms where halal authorities and regulators act as validating nodes, enabling smart-contract-based certificate management and auditing. By storing cryptographic hashes rather than raw data, the blockchain layer serves as a trust-and-integrity anchor without becoming a scalability bottleneck.

5. CONCLUSION

This research presents an integrated Multimodal Explainable Artificial Intelligence (MXAI) and blockchain framework for automated halal verification of cosmetic products. The proposed system combines ingredient information extracted through OCR, manually entered label text, and visual product-label features to classify products into halal, haram, or syubhat categories. The MXAI component improves decision transparency by providing explainable classification outputs, while the blockchain component strengthens traceability, integrity, and auditability through SHA-256 hashing, Merkle root verification, and QR-code-based certificate access. The experimental results show that the proposed fusion model achieved an accuracy of 94.5%, outperforming the text-only BERT and image-only CNN baselines. These findings indicate that integrating explainable AI with blockchain can improve trust in automated halal verification by making the classification process more accurate, transparent, and tamper-evident. The framework can be further extended to other halal supply chain sectors that require reliable product authentication, accountable decision-making, and secure digital certification.

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