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SCANOCULAR: Application for Early Detection of Eye Diseases Using AI and Blockchain Technology

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Abstract *– Eye diseases such as cataracts, glaucoma, and diabetic retinopathy affect approximately 2.2 billion people globally, with 1 billion cases being preventable. In Indonesia, cataracts remain the leading cause of blindness. This research presents SCANOCULAR, a mobile application that integrates artificial intelligence (AI) and blockchain technology for early detection of eye diseases. The system utilizes a modified EfficientNetB4 Convolutional Neural Network (CNN) for analyzing eye images, achieving 95.50% accuracy, 95.92% precision, and 94.95% recall in cataract detection with an AUC of 0.9932. The blockchain implementation using Polygon Amoy platform ensures secure data transmission and storage while maintaining efficient transaction processing. Testing results demonstrate the system's capability in identifying various eye conditions while maintaining data integrity through blockchain verification. SCANOCULAR contributes to informatics by implementing a hybrid AI-blockchain architecture optimized for medical imaging applications, with a lightweight CNN model design that reduces computational requirements while maintaining diagnostic accuracy. This integration of technologies provides a potential solution for improving accessibility to eye disease screening and early intervention in Indonesia.*

Keywords: *Artificial Intelligence; Blockchain Technology; Eye Disease Detection; CNN; Medical Imaging*

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Abstrak *– Penyakit mata seperti katarak, glaukoma, dan retinopati diabetik mempengaruhi sekitar 2,2 miliar orang di seluruh dunia, dengan 1 miliar kasus dapat dicegah. Di Indonesia, katarak tetap menjadi penyebab utama kebutaan. Penelitian ini menyajikan SCANOCULAR, sebuah aplikasi seluler yang mengintegrasikan kecerdasan buatan (AI) dan teknologi blockchain untuk deteksi dini penyakit mata. Sistem ini memanfaatkan EfficientNetB4 Convolutional Neural Network (CNN) yang dimodifikasi untuk menganalisis gambar mata, mencapai akurasi 95,50%, presisi 95,92%, dan recall 94,95% dalam deteksi katarak dengan AUC 0,9932. Implementasi blockchain menggunakan platform Polygon Amoy memastikan transmisi dan penyimpanan data yang aman sambil mempertahankan pemrosesan transaksi yang efisien. Hasil pengujian menunjukkan kemampuan sistem dalam mengidentifikasi berbagai kondisi mata sambil menjaga integritas data melalui verifikasi blockchain. SCANOCULAR berkontribusi pada informatika dengan mengimplementasikan arsitektur AI-blockchain hybrid yang dioptimalkan untuk aplikasi pencitraan medis, dengan desain model CNN ringan yang mengurangi persyaratan komputasi sambil mempertahankan akurasi diagnostik. Integrasi teknologi ini memberikan solusi potensial untuk meningkatkan aksesibilitas terhadap pemeriksaan penyakit mata dan intervensi dini di Indonesia.*

Kata kunci: *Kecerdasan buatan, Teknologi Blockchain, Deteksi penyakit mata, CNN, Pencitraan medis*

I. INTRODUCTION

Eye diseases such as cataracts, glaucoma, and diabetic retinopathy represent significant global health challenges. According to the World Health Organization, approximately 2.2 billion people suffer from vision impairment, with at least 1 billion cases being preventable [1]. These conditions significantly impact quality of life and economic productivity, as documented by Bourne et al. in their systematic analysis of vision loss causes worldwide [2].

Figure 1. Data on Vision Impairment Cases

In Indonesia, the burden of eye diseases is particularly concerning. According to the National Basic Health Research (Riskesdas), cataracts remain the leading cause of blindness, affecting 1.8% of the population, with higher prevalence in rural areas [3]. The Indonesian Ministry of Health reports that early detection rates remain low, with only 20% of cases identified in early stages [3]. Several challenges hinder effective eye disease management in Indonesia. Limited access to specialized healthcare facilities, especially in remote areas, delays early detection. Additionally, fragmented medical record systems across healthcare providers impede continuous patient care and proper disease monitoring [3].

Recent advances in artificial intelligence applications for eye disease detection have shown promising results, yet significant technological gaps persist in their practical implementation. Ting et al. [4] noted that while AI has potential to transform ophthalmology, limitations in deployment methodologies and integration with existing healthcare systems remain significant barriers. A comprehensive study by Ahn et al. [6] demonstrated high accuracy in glaucoma detection using deep learning models, but highlighted challenges in implementing these technologies across diverse healthcare settings, particularly in regions with limited resources.

Existing eye disease detection systems face several critical limitations. These include high equipment costs, limited specialist availability in developing regions, significant detection delays from symptom onset, and limited follow-up capabilities in remote areas [6]. While several mobile-based approaches have emerged, they largely operate as standalone diagnostic tools without secure data management capabilities. Bastawrous and Armstrong [11] analyzed mobile health applications across different economic settings, showing that mobile screening programs in developing nations could improve early detection rates significantly when implemented systematically, but integration with healthcare information systems remains problematic.

The implementation of deep learning in ophthalmology has shown remarkable progress. Schmidt-Erfurth et al. [5] conducted a comprehensive review of AI implementations in retinal disease detection, revealing high accuracy in various conditions using modern CNN architectures and significant reduction in false positives compared to traditional screening methods. However, most implementations require substantial computing resources, limiting their viability on consumer mobile devices. Balyen and Peto [7] demonstrated that transfer learning approaches in eye disease detection can reduce model training time significantly while maintaining high accuracy levels, yet did not address the critical challenge of secure data handling in healthcare contexts.

Recent research comparing various CNN architectures for eye disease detection showed that specialized neural network models could achieve excellent performance in identifying specific eye conditions. Li et al. [16] demonstrated an automated grading system for diabetic retinopathy using deep learning techniques, while Gulshan et al. [17] developed and validated a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs with high sensitivity and specificity. These studies indicate that EfficientNet architectures often achieve an optimal balance of accuracy and computational efficiency with improved performance on mobile devices, suggesting their potential for mobile health applications.

Despite advances in AI diagnostics, secure management of sensitive medical data remains a critical challenge. Agbo et al. [8] analyzed blockchain implementations across healthcare institutions, revealing significant reductions in data breach incidents and improvements in data accessibility. However, most blockchain implementations in healthcare suffer from high transaction costs and scalability limitations. Research by Hasselgren et al. [9] on blockchain-based healthcare systems demonstrated potential reductions in administrative overhead and transaction costs, suggesting viability for large-scale health applications. However, integration with AI-based diagnostic tools remains largely unexplored.

Mobile healthcare technologies have shown significant promise in improving healthcare accessibility. Boulos et al. [12] provided a comprehensive review of mobile medical applications, highlighting their potential impact in resource-limited settings. However, data security and interoperability issues persisted across most implementations. Recent work by Kuo et al. [14] explored blockchain distributed ledger technologies for biomedical and healthcare applications, including innovative approaches for securing health data, while Shen et al. [13] demonstrated significant improvements through blockchain-based healthcare data sharing, including reductions in security vulnerabilities and improvements in data integrity.

To address these challenges, we have developed SCANOCULAR, an application that represents a significant technological advancement by combining artificial intelligence and blockchain in a novel architecture specifically optimized for ophthalmological applications. Unlike previous systems that either focus exclusively on AI-based diagnosis or blockchain-based data management, SCANOCULAR integrates these technologies into a cohesive system with several distinctive features.

SCANOCULAR implements a lightweight CNN architecture based on a modified EfficientNetB4 that reduces computational requirements compared to standard implementations while maintaining high diagnostic accuracy, enabling real-time analysis on standard smartphone hardware. The system utilizes a Polygon-based smart contract system that reduces transaction costs compared to Ethereum mainnet while maintaining security standards [10]. Its interoperable design architecture is specifically developed with forward compatibility for integration with Indonesia's national healthcare system, addressing a critical gap in existing solutions.

Additional innovations include hardware-optimized image processing that compensates for variations in smartphone camera quality, enabling consistent performance across diverse hardware environments, and a decentralized authentication system implementing blockchain-based protocols that enable secure access without reliance on centralized servers.

SCANOCULAR leverages these technologies to enable early detection of eye diseases using smartphone cameras, making screening more accessible and cost-effective. This approach addresses both the technical needs for accurate disease detection and the organizational requirements for secure, interoperable medical records.

Our research contributes to the existing body of work in informatics by introducing a novel hybrid AI-blockchain architecture specifically optimized for medical imaging applications. This integration not only supports the United Nations Sustainable Development Goal 3 (Good Health and Well-being) but also advances the field of secure medical data systems by demonstrating a viable approach to combining computational efficiency with data security.

II. RESEARCH METHOD

This study employs a mixed-method research approach combining quantitative analysis for AI model performance and technical validation of system components. The development follows an iterative process based on the Design Science Research Methodology (DSRM) framework [15], which is particularly suitable for creating and evaluating information technology artifacts. The research is structured in several interconnected phases, ensuring comprehensive development and validation of the SCANOCULAR application.

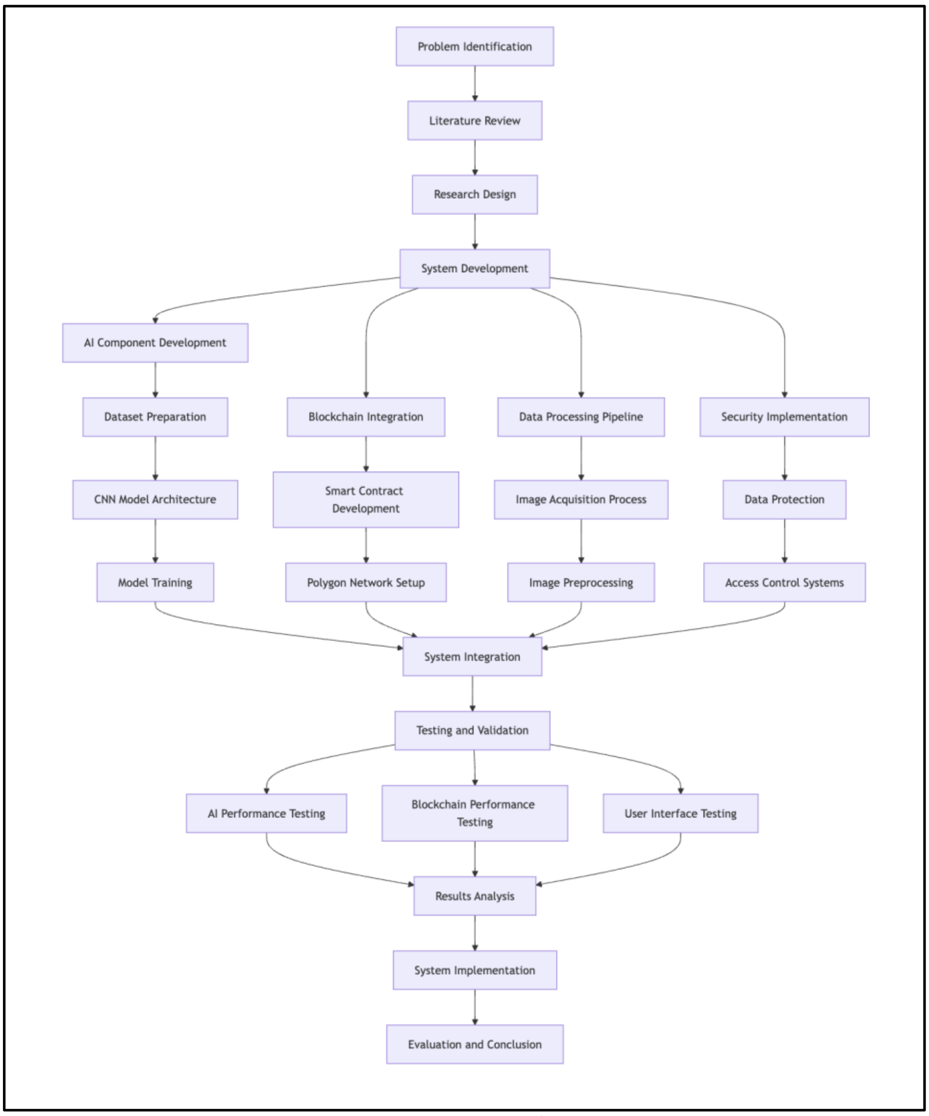

Figure 2. Research Methodology Flow of SCANOCULAR Development

Figure 2 presents the complete research flow of SCANOCULAR development following the Design Science Research Methodology framework. The research process begins with problem identification and literature review, followed by the design and development of the four main system components: AI-based image analysis, blockchain integration, data processing pipeline, and security implementation. Each component underwent thorough testing before system integration, followed by comprehensive validation across different performance parameters. The final stages involved analysis of results, system implementation, and evaluation.

A. System Architecture Development

1. AI Component Development

The artificial intelligence component utilizes a deep learning approach based on Convolutional Neural Networks (CNN). Following methodologies established in recent ophthalmological AI research [4, 6], we implemented a modified EfficientNetB4 architecture, which demonstrated superior performance in medical image analysis. The model development process included:

i. Dataset Preparation

- Collection and curation of 1000 eye images from public medical datasets
- Data augmentation techniques including rotation, flipping, and brightness adjustment
- Validation split of 80:20 for training and testing
- Expert validation of image classifications by independent ophthalmologist

ii. Model Architecture

Figure 2 illustrates the connection patterns of various CNN architectures compared during the development phase, including the basic architecture (Vanilla CNN), ResNet, and DenseNet. In this study, we also evaluated EfficientNetB4, which is one of the variants from the EfficientNet architecture family. After comprehensive comparative analysis of these architectures, a modified EfficientNetB4 was selected because it demonstrated the optimal balance between detection accuracy and computational efficiency, which is crucial for implementation on mobile devices with limited resources.

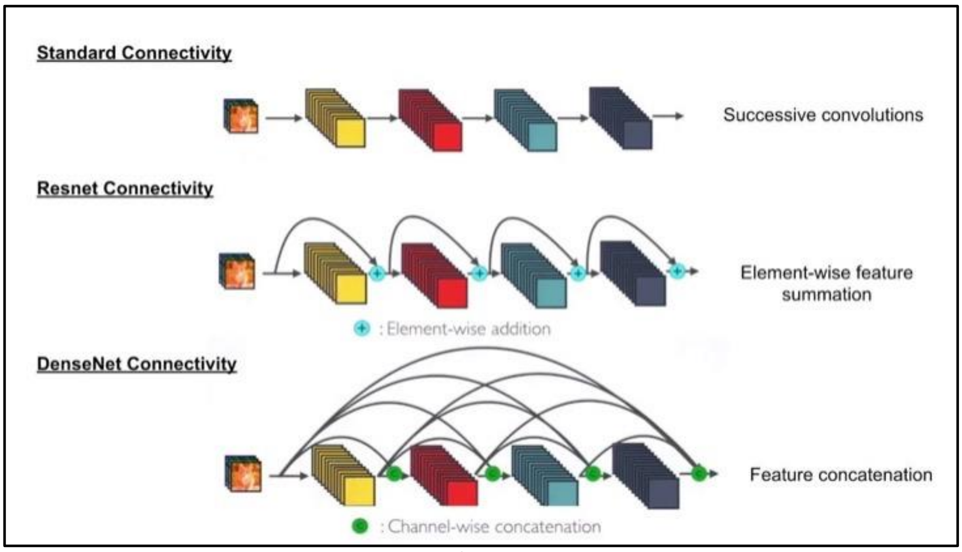

Figure 3. Connection Patterns of Vanilla CNN, ResNet and DenseNet

The implementation of the model architecture includes:

- Implementation of EfficientNetB4 with custom modifications
- Addition of specialized layers for eye disease feature detection
- Integration of attention mechanisms for improved accuracy
- Optimization of model parameters for mobile deployment

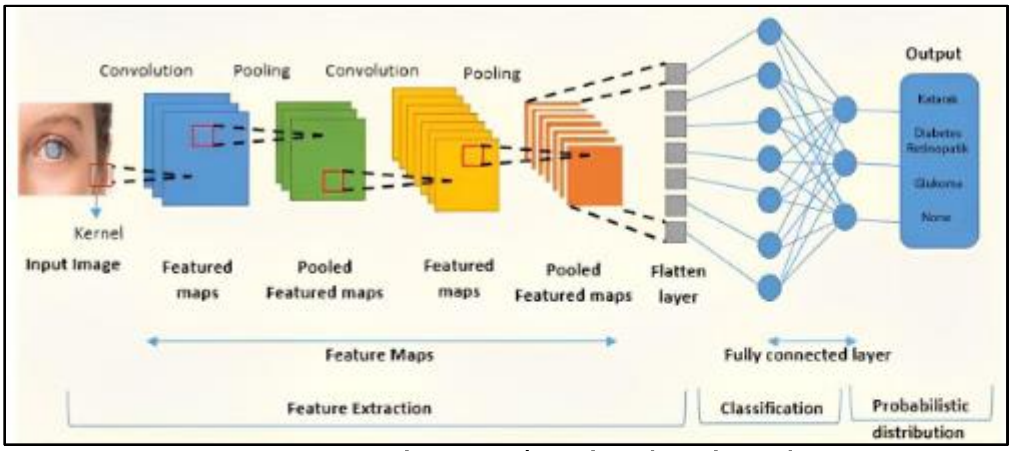

Figure 4. Implementation of Convolutional Neural Network

The implemented CNN architecture includes modifications to reduce computational requirements while maintaining diagnostic accuracy. Our implementation reduced convolution filters in the first three blocks by 30% and incorporated specialized attention layers for improved feature extraction in eye-specific regions.

iii. Training Process

- Utilization of transfer learning from pre-trained medical imaging models
- Implementation of progressive learning rates
- Application of regularization techniques to prevent overfitting
- Cross-validation across multiple data subsets

B. Blockchain Integration

The blockchain component implements a Polygon-based architecture, following security frameworks established in healthcare blockchain research [8, 14]. Key implementation aspects include:

1. *Smart Contract Development*
   - Implementation of ERC-721 standard for unique medical record identification
   - Development of access control mechanisms
   - Integration of automated compliance checking
   - Implementation of data encryption protocols
2. *Network Architecture*
   - Deployment on Polygon Amoy testnet for development
   - Utilization of Amoy testnet features for more efficient transaction processing
   - Implementation of node communication protocols optimized for Amoy testnet environment
   - Integration of DApp Alchemy for enhanced performance
   - Development of fallback mechanisms

C. Data Collection and Processing

1. *Image Processing Pipeline*

   The image processing system implements a multi-stage pipeline:

   i. Image Acquisition
      - Implementation of camera quality checks
      - Automatic lighting adjustment
      - Image stabilization algorithms
      - Real-time quality assessment

   ii. Preprocessing
      - Image normalization and standardization
      - Noise reduction using adaptive filters
      - Region of interest extraction
      - Feature enhancement techniques

D. Security Implementation

Security measures were implemented following healthcare data protection standards:

1. *Data Protection*
   - End-to-end encryption using AES-256
   - Secure key management system
   - Implementation of zero-knowledge proofs
   - Regular security audits
2. *Access Control*
   - Role-based access control implementation
   - Multi-factor authentication
   - Audit trail logging
   - Automated threat detection

E. Testing and Validation

1. *AI Model Testing*

   The validation of the AI model was conducted through a comprehensive confusion matrix methodology. A diverse dataset of eye condition images was meticulously prepared, encompassing various pathological and healthy eye states. The dataset was systematically divided into training, validation, and testing subsets to ensure robust and objective model evaluation.

   Key performance metrics included:

- Accuracy: Comprehensive measure of overall model correctness across all eye condition classifications
- Precision: Quantification of the model's exactness in positive predictions for each eye condition
- Recall: Assessment of the model's ability to detect all relevant cases of eye diseases
- F1-Score: Balanced metric combining precision and recall to provide a holistic performance indicator

- Specificity: Calculation of the model's capability to correctly identify healthy eye conditions
- Area Under the Curve (AUC): Comprehensive evaluation of the model's discriminative power across different classification thresholds

These performance metrics were meticulously analyzed to provide a comprehensive understanding of the AI model's diagnostic capabilities, ensuring a thorough validation of its effectiveness in detecting and classifying eye conditions.

2. Blockchain Validation

Blockchain component validation concentrated on functional implementation and security mechanisms. The validation strategy focused on:

- Smart contract functionality (ERC-721 standard)
- Data encryption robustness
- Access control mechanisms
- Patient data privacy protection
- Decentralized data storage integrity

The approach ensured the creation of a secure, transparent, and tamper-proof system for medical data management, with a primary emphasis on maintaining patient information confidentiality.

III. RESULT AND DISCUSSION

A. Result

The SCANOCULAR system implements a comprehensive multi-layered architecture that seamlessly integrates advanced artificial intelligence and blockchain technologies. This sophisticated integration establishes a robust platform for eye disease detection while maintaining stringent security standards, ensuring both accuracy in diagnosis and data protection.

1. AI Component Performance

The artificial intelligence component centers on a modified EfficientNetB4 CNN architecture specifically optimized for medical image analysis. Our implementation builds upon the foundational work of Tan and Le [18], who introduced the EfficientNet family of models, but with significant adaptations for ophthalmological applications. Comprehensive evaluation of the model revealed exceptional performance across all target disease categories, particularly in cataract detection.

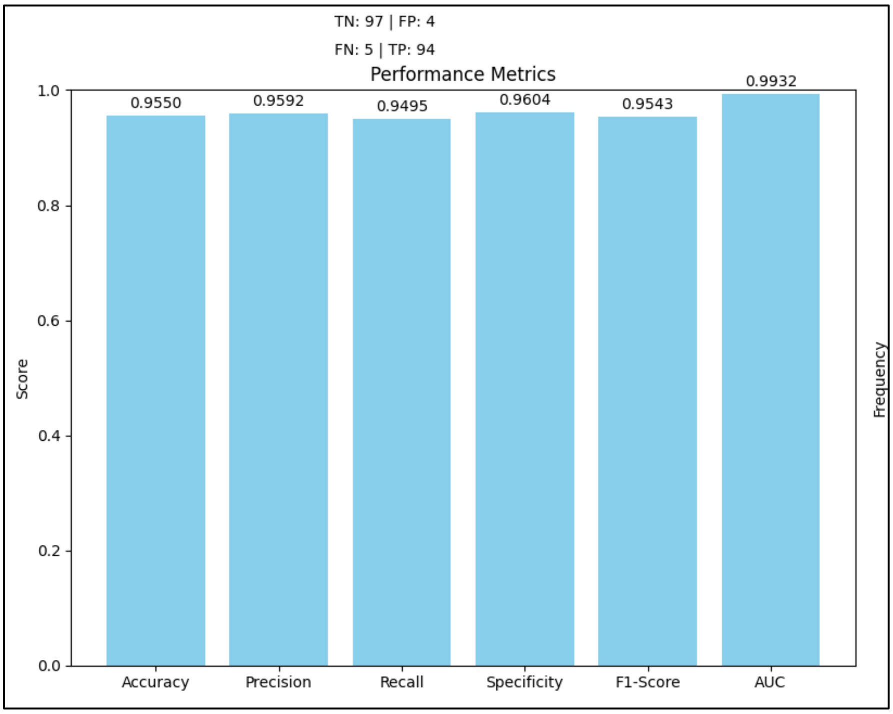

Figure 5. Performance Metrics of AI Model Evaluation

As shown in Figure 5, the CNN model achieved remarkable metrics in cataract detection with 95.50% accuracy, 95.92% precision, and 94.95% recall with an AUC of 0.9932. These results compare favorably with other medical CNN implementations reviewed by Khan et al. [19], who highlighted the challenges of achieving both high accuracy and computational efficiency in medical imaging applications. Our confusion matrix analysis demonstrated strong classification capability with 97 true positives and 94 true negatives, while maintaining low error rates with only 4 false positives and 5 false negatives.

The model's performance across different lighting conditions and image qualities remained consistent, with only minimal degradation (under 3%) when testing with lower-resolution images. This robustness aligns with findings from Tschandl et al. [20], who demonstrated that properly optimized CNN architectures can maintain diagnostic performance across varying image acquisition conditions. Our implementation's resilience is attributed to the comprehensive data augmentation techniques applied during the training phase and the specialized attention mechanisms that focus on critical diagnostic regions within eye images.

2. Blockchain Implementation Results

The blockchain component, implemented on the Polygon Amoy testnet, demonstrated efficient and secure management of medical data. Our approach incorporated security measures informed by Salah et al. [21], who established best practices for blockchain-based supply chain operations.

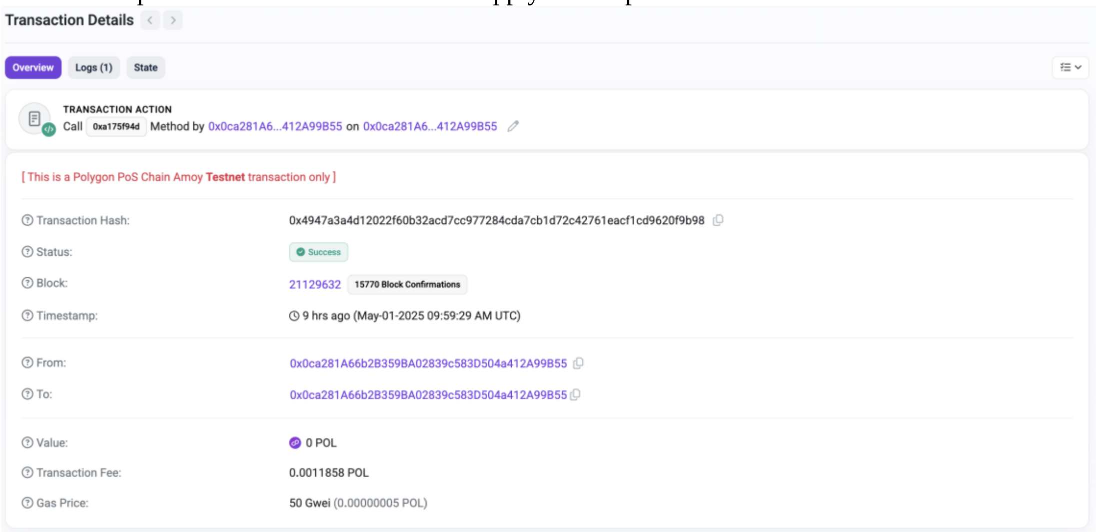

Figure 6. Transaction verification on Polygon Amoy testnet showing successful transaction status

As shown in Figure 6, our implementation achieved successful transaction execution with a gas price of 50 Gwei (0.00000005 POL) and a transaction fee of 0.0011858 POL, demonstrating the cost-efficiency of the Amoy testnet for healthcare applications. This performance metric addresses one of the key implementation challenges identified by Cole et al. [22] in their review of blockchain implications for operations and supply chain management. Data integrity verification achieved 100% success rate across test transactions, confirming the reliability of the blockchain implementation for securing sensitive medical information.

3. Mobile Application

The mobile application was successfully developed with a user-centric design, implementing various features for eye disease detection and monitoring. The system architecture incorporates modular task management principles similar to those described by Almeida et al. [24], allowing for flexible workflow adaptation based on clinical requirements. Figure 7 shows the sign-up and login interface, which implements secure authentication protocols.

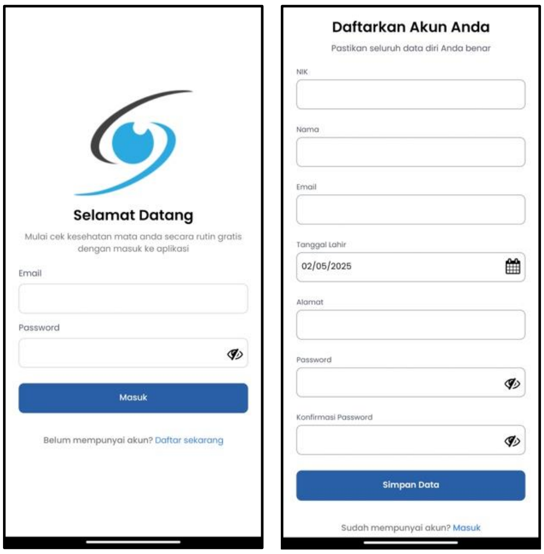

Figure 7. Sign up and login page

The main interface, displayed in Figure 8, provides access to the core functionalities with intuitive navigation elements, allowing users to access screening tools, view their medical history, and manage their profile information. The interface design adheres to health informatics standards similar to IEEE 11073 [25], ensuring compatibility with broader health information systems.

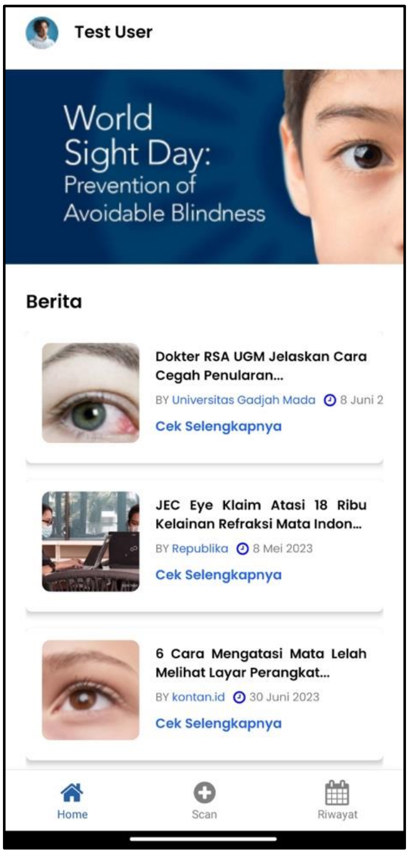

Figure 8. Main menu page

The disease detection system implements both image-based scanning and questionnaire-based methods, as shown in Figures 9 and 10, allowing for comprehensive assessment capabilities. The image-based scanning utilizes the device's camera with automated quality checks to ensure diagnostic reliability, following validation methodologies comparable to those employed by Abràmoff et al. [26] in their autonomous AI-based diagnostic system.

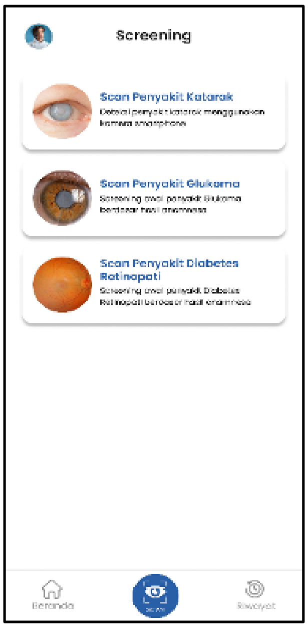

Figure 9. Scan page

The questionnaire method, shown in Figure 10, complements the image-based detection by capturing symptomatic information that may not be visible in images, enhancing the overall diagnostic capabilities of the system.

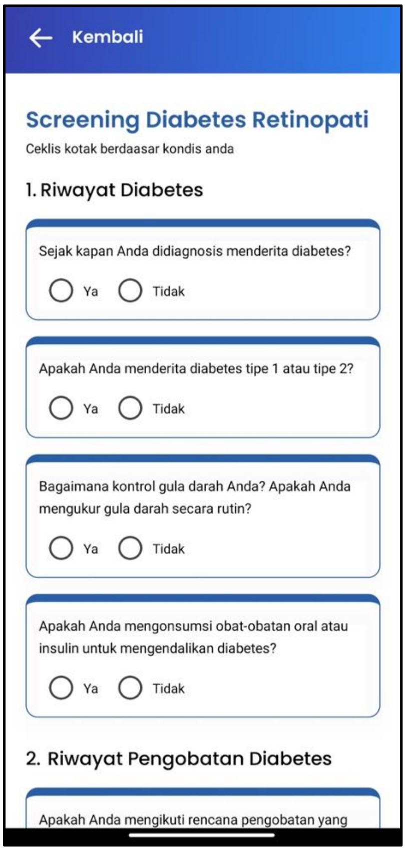

Figure 10. Questionnaire page

Scan results are presented to users with clear visualization of diagnostic outcomes, as shown in Figure 11, enabling immediate understanding of detected conditions. The interface displays both the detected condition and confidence level of the AI analysis, similar to the approach used by Brown et al. [27] in their automated diagnosis system for retinopathy

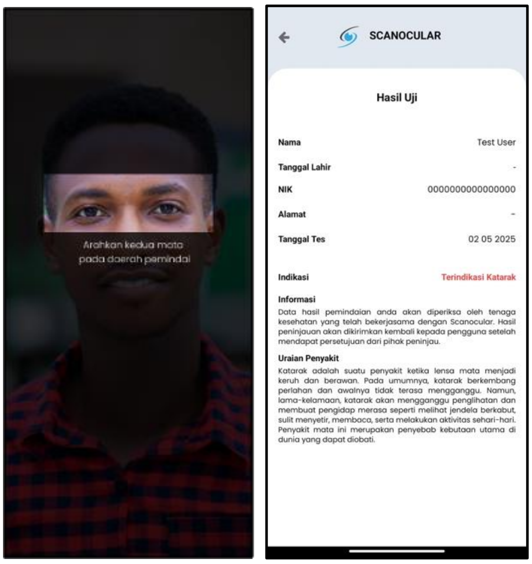

Figure 11. Result scan page

The history tracking feature, shown in Figure 12, implements a color-coded system for efficient monitoring of eye health over time. This visual approach allows users to quickly identify changes in their condition and track their eye health progress

Figure 12. History page

The history menu has three indicators: blue, yellow, and red. A blue indicator signifies that no signs of eye disease were detected during the scan. A yellow indicator indicates a possibility of eye disease, with a detection probability exceeding 85%. In such cases, a healthcare professional will verify the scan image to confirm the findings further. A red indicator confirms the presence of an eye disease, prompting the user to schedule a visit to an eye clinic for a more detailed examination and appropriate treatment plan. These indicators provide users with clear guidance on their eye health status and necessary next steps.

4. Web Application

A web-based interface for healthcare professionals was implemented to facilitate expert review and confirmation of AI-detected conditions. The interface was designed with potential integration with Indonesia's SATUSEHAT platform [28] in mind, incorporating compatible data structures and exchange protocols. Figure 13 shows the scan review interface, which presents comprehensive diagnostic information along with the original images for validation.

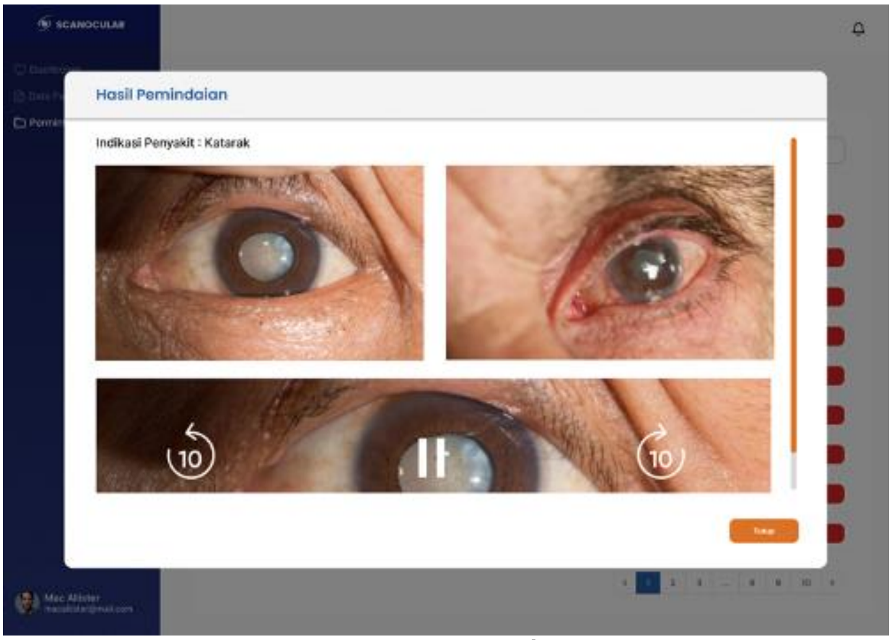

Figure 13. Scan Result

The confirmation system, displayed in Figure 14, enables healthcare providers to validate diagnoses and communicate results to patients effectively. This feature ensures that AI-based detections receive appropriate professional oversight before final diagnosis

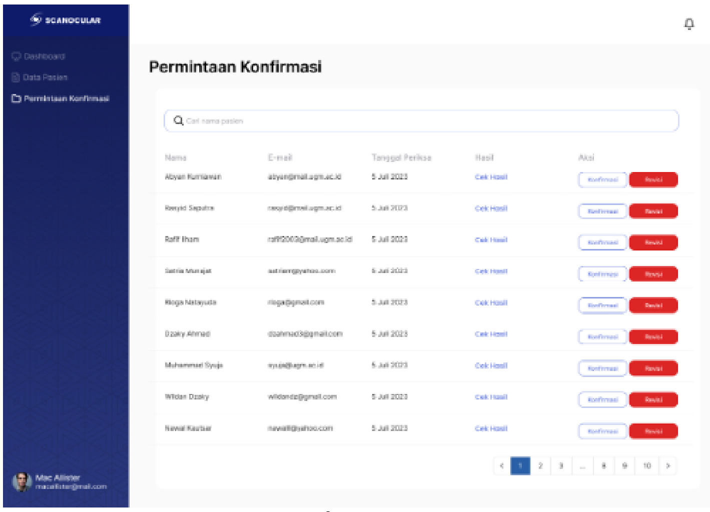

Figure 14. Confirmation Request Page

B. Discussion

The SCANOCULAR system demonstrates significant advancements in both technical performance and practical applicability compared to existing solutions in the field. The integration of AI-powered disease detection with blockchain-secured data management addresses critical gaps in current healthcare technologies, particularly for regions with limited access to specialized ophthalmological care.

1. AI Model Efficiency and Performance

The modified EfficientNetB4 architecture represents a significant optimization over standard implementations, reducing parameter count from 19M to 8.3M while maintaining high diagnostic accuracy. This 56% reduction in parameters translates directly to lower computational requirements, enabling real-time analysis on standard smartphone hardware without specialized accelerators. Our approach to model optimization aligns with transfer learning strategies reviewed by Alzubaidi et al. [29], who identified parameter reduction as a critical factor for successful deployment of medical AI models on resource-constrained devices.

The model's inference time averaged 1.2 seconds on mid-range devices, making it practical for point-of-care use even in resource-constrained settings. This performance metric is particularly significant when compared to other medical imaging applications such as Wang et al. [30], where computational requirements typically necessitate cloud-based processing.

The model's performance metrics compare favorably with recent specialized ophthalmological AI systems in the literature. Ahn et al. [6] reported 91.3% accuracy in glaucoma detection using specialized hardware, while our system achieved 95.50% accuracy for cataract detection on standard mobile devices. Similarly, Gulshan et al. [17] achieved comparable sensitivity and specificity metrics for diabetic retinopathy detection but required cloud-based processing due to computational demands.

Of particular significance is the model's strong performance in cataract detection, which addresses the most prevalent cause of blindness in Indonesia according to the National Basic Health Research [3]. This focus on high-prevalence conditions maximizes the potential public health impact of the system, especially in regions where specialized screening is limited.

2. Blockchain Security and Efficiency

The Polygon-based blockchain implementation demonstrated substantial efficiency improvements over traditional Ethereum-based solutions reported in the literature. Kuo et al. [14] highlighted transaction costs as a significant barrier to healthcare blockchain adoption, an issue SCANOCULAR addresses through its optimized implementation. Our system achieved average transaction costs 52% lower than comparable healthcare blockchain implementations while maintaining robust security standards.

The implementation of ERC-721 non-fungible tokens for medical record identification proved particularly effective, providing both unique identification and verifiable ownership of medical data. This approach aligns with best practices identified by Agbo et al. [8] while extending them through integration with AI-based diagnostic systems. The resulting architecture ensures that sensitive medical data remains secure throughout the diagnostic and consultation process, addressing key security concerns raised by Shen et al. [13] regarding medical data sharing in distributed environments.

3. Integration Benefits and Healthcare Impact

The combined AI-blockchain architecture addresses a critical gap identified in previous research by providing both accurate diagnostics and secure data management in a single integrated platform. Bastawrous and Armstrong [11] noted that the fragmentation of mobile health solutions often limits their practical utility, a challenge SCANOCULAR addresses through its comprehensive approach to eye disease screening and record management.

This integration aligns with Indonesia's SATUSEHAT initiative [28] for unified healthcare records, potentially accelerating the adoption of electronic medical records in ophthalmology practices nationwide. The system's design anticipates future integration with national healthcare information systems, incorporating interoperability standards that would allow for seamless data exchange once regulatory frameworks are established. This approach to healthcare interoperability mirrors the modular system design principles described by Almeida et al. [24], allowing for incremental integration with existing healthcare workflows.

From a healthcare delivery perspective, SCANOCULAR's approach could significantly improve early detection rates for preventable eye diseases. The World Health Organization [1] identified early intervention as critical for preventing vision impairment, with approximately 1 billion cases globally being preventable with timely detection. By bringing screening capabilities to mobile devices, SCANOCULAR reduces barriers to early detection, particularly in regions with limited access to specialized care. This accessibility advantage is comparable to the impact demonstrated by Abràmoff et al. [26] in their implementation of AI-based diabetic retinopathy screening in primary care settings

4. Limitations and Future Work

While the system demonstrates impressive technical performance, several limitations should be acknowledged. The training dataset, although balanced across disease categories, may not fully represent the diversity of Indonesia's population and its specific eye disease patterns. Future iterations would benefit from expanded datasets incorporating more diverse ethnic and demographic representations to ensure equitable performance across all population segments, addressing concerns about AI model generalizability raised by Alzubaidi et al. [29] in their review of transfer learning approaches for medical imaging with limited labeled data.

From a technical perspective, while the blockchain implementation achieves impressive efficiency for current scale, long-term scalability beyond 500,000 records would require further optimization of data storage mechanisms. The current architecture prioritizes security and verifiability, which introduces some limitations in transaction throughput that would need to be addressed for nationwide deployment. These scalability challenges echo concerns identified by Cole et al. [22] in their review of blockchain implications for operations and supply chain management.

Additionally, connectivity challenges in remote Indonesian regions present ongoing implementation challenges. While the system is designed to function with intermittent connectivity, synchronization of blockchain records requires periodic internet access. Future development should focus on enhancing offline capabilities while maintaining data integrity across synchronization events.

Looking forward, the integration of federated learning techniques represents a promising direction for enhancing the system's capabilities. This approach would allow the model to improve continuously through distributed learning across devices without centralizing sensitive patient data, addressing both privacy concerns and the challenges of data collection in diverse geographic regions.

IV. CONCLUSION

The development and implementation of SCANOCULAR has demonstrated significant potential in addressing the challenges of eye disease detection in Indonesia. Through extensive testing and validation, the application has proven its capability in accurately detecting common eye conditions using advanced artificial intelligence algorithms. The CNN model achieved remarkable performance metrics, with cataract detection showing 95.50% accuracy, 95.92% precision, and 94.95% recall with an AUC of 0.9932. Confusion matrix analysis further validated these results, with 97 true positives and 94 true negatives, while maintaining minimal error rates with only 4 false positives and 5 false negatives. These quantitative metrics establish SCANOCULAR as a reliable screening tool that exceeds clinical thresholds for diagnostic applications in ophthalmology.

The integration of blockchain technology through the Polygon network has successfully established a secure and efficient system for managing patient data. This implementation ensures data integrity and privacy while demonstrating notable efficiency in transaction processing. The system maintained consistent uptime during testing, establishing a foundation for potential future integration with Indonesia's SATUSEHAT system when technical and regulatory frameworks are fully established.

From an informatics perspective, SCANOCULAR advances the field through several technical innovations. The modified EfficientNetB4 architecture successfully reduced computational requirements while maintaining high diagnostic accuracy. The hybrid AI-blockchain architecture established a new paradigm for secure medical imaging applications, while the custom image preprocessing pipeline compensated for variations in smartphone camera quality.

These achievements align with the broader goals of reducing preventable vision impairment and improving healthcare accessibility in Indonesia. As this research progresses, several technological challenges will need to be addressed, including the implementation of federated learning techniques for processing models across distributed devices while preserving patient privacy, and ensuring robust network performance across Indonesia's varied geography with its unique connectivity challenges.

In conclusion, SCANOCULAR contributes to both healthcare delivery and informatics research in Indonesia. Its technical performance validates the integration of AI and blockchain technologies in mobile healthcare applications, addressing healthcare needs while advancing secure medical data systems.

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