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Integrating Blockchain with Neural Networks for Forest Fire Classification

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Abstract: Forest fires represent one of the most severe environmental disasters, causing extensive ecological, social, and economic damage—particularly in tropical nations like Indonesia. This research introduces a hybrid framework that combines Blockchain and Neural Network technologies to classify forest fire images. The goal is not only to enhance detection precision but also to guarantee the integrity and security of experimental data. Two deep learning architectures, ResNet-50 and VGG-16, were implemented and evaluated to compare their effectiveness in differentiating fire from non-fire imagery. The dataset merges locally collected images from the Puncak area of Bogor, Indonesia, with the public FIRE dataset from Kaggle, thereby increasing model generalization. Model training utilized a transfer learning strategy, and its performance was assessed through four key indicators: accuracy, precision, recall, and F1-score. The findings demonstrate that VGG-16 achieved the most reliable outcomes, obtaining an accuracy of 0.91 and an F1-score of 0.87, outperforming ResNet-50, which reached 0.82 accuracy. All experimental data, including training and inference outputs, were stored using the InterPlanetary File System (IPFS), while each file's Content Identifier (CID) and metadata were recorded in a blockchain-based smart contract to ensure transparency, verifiability, and data permanence. The study concludes that integrating blockchain with deep learning establishes a trustworthy and tamper-resistant framework for forest fire image classification. Future research may explore lighter CNN models and the fusion of IoT sensor data to enable adaptive and real-time fire detection.

Keywords: Forest Fires, Blockchain, Neural Network, ResNet-50, VGG-16, IPFS, Smart Contract

INTRODUCTION

Forest fires are among the most devastating environmental disasters, exerting profound impacts on ecosystems, human health, and the economy. In Indonesia, this phenomenon occurs almost every year, particularly in Sumatra and Kalimantan, where extensive tropical forests are highly vulnerable to prolonged dry seasons. According to the Ministry of Environment and Forestry (2024), more than one million hectares of forest areas are burned annually, leading to massive financial losses and elevated carbon emissions. The adoption of artificial intelligence (AI) technologies, especially deep learning, has introduced new opportunities for the early identification of forest fires through the analysis of satellite and aerial imagery. One of the most effective approaches is the Convolutional Neural Network (CNN), recognized for its capability to automatically extract complex visual patterns from image data. As reported by Dwiputra et al. (2023), CNN architectures such as VGG-16, Inception-V3, and ResNet-50 have shown excellent performance in forest fire image classification, while Zhang et al. (2023) demonstrated improvements in small-object detection accuracy using a Faster RCNN model based on ResNet-50.

Although CNN demonstrates strong performance, its practical implementation still encounters several significant challenges. The accuracy of the model often deteriorates due to variations in image quality and the visual similarity between smoke, fog, and cloud formations, which complicates accurate classification. Additionally, the centralized storage of training datasets and model outputs is susceptible to manipulation or data loss, posing risks to data integrity. Moreover, transparency and traceability in machine learning research are frequently neglected, making replication and validation more difficult. These limitations emphasize the need for a system that not only focuses on enhancing classification accuracy but also ensures the authenticity, reliability, and security of data throughout the entire research process.

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To address these limitations, this study proposes an integration of Blockchain technology with Neural Network architectures for forest fire image classification. The concept draws inspiration from prior implementations of blockchain in geospatial data management and decision support systems (DSS), such as the TOPSIS-based landslide mitigation framework developed by Hindarto et al. (2025) and the Blockchain-Driven Multi-Criteria DSS introduced by Cahyo and Hindarto (2025) for forest fire monitoring. In this research, the preprocessed image dataset is stored in the InterPlanetary File System (IPFS) to ensure decentralized and immutable data management. Furthermore, two CNN architectures ResNet-50 and VGG-16 are trained and evaluated using metrics such as accuracy, precision, recall, and F1-score. All model outputs and prediction results are uploaded to IPFS and linked through smart contracts on the blockchain to maintain integrity and transparency.

A review of the existing literature reveals that many studies have examined CNN-based forest fire detection and the use of blockchain for geospatial data protection. However, none have combined the two technologies into a single, integrated framework that provides transparent validation and auditability of experimental outcomes. Most prior works concentrate solely on enhancing model accuracy or discuss blockchain applications conceptually, without merging them into a unified system. This research addresses that gap by presenting an end-to-end framework that fuses machine learning with distributed ledger technology (DLT) to achieve a verifiable, secure, and reproducible classification pipeline for forest fire imagery.

The novelty of this study lies in its unified system design that connects CNNs, IPFS, and blockchain into a transparent and auditable ecosystem. This work extends the crypto-spatial framework previously introduced by Hindarto and Hariadi (2024) for landslide risk mapping and applies it to forest fire detection using image data. Beyond achieving high classification accuracy, this study prioritizes the preservation of data integrity and experimental reliability through permanent blockchain recording. The objectives of this research are threefold: (1) to compare the performance of ResNet-50 and VGG-16 architectures in classifying forest fire images; (2) to employ IPFS and smart contracts to guarantee data security and traceability; and (3) to establish a replicable and credible research framework that aligns with the principles of scientific transparency. This integrated approach is expected to support the creation of intelligent, secure, and sustainable forest fire detection systems.

LITERATURE REVIEW

Research Studies concerning forest fire image classification and the integration of blockchain into decision-support systems have expanded significantly in recent years. This section reviews six recent and relevant publications closely related to this research, focusing on the implementation of deep learning for image classification and the utilization of blockchain for securing and ensuring data transparency.

The study by Dwiputra et al. (2023) compared three CNN architectures VGG16, Inception-V3, and ResNet-50 for classifying fire and non-fire images using a dataset of 952 samples. The findings revealed that Inception-V3 attained the highest accuracy of 98%, while VGG16 demonstrated stable and consistent results, and ResNet-50 showed slightly lower performance. Although this work validates the effectiveness of CNN models for forest fire classification, it does not address the issues of data integrity and model security, which are key aspects developed further in the present research.

From the blockchain perspective, Hindarto et al. (2025) introduced a blockchain-based landslide mitigation framework employing the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to enhance transparency and reliability in decision-making. This system ensures secure and immutable storage of geospatial data through smart contracts on the blockchain. The approach directly inspired this study to adopt similar concepts for maintaining the authenticity of datasets and classification results in forest fire detection.

In another contribution, Hindarto et al. (2025) presented the Blockchain and Multi-Criteria Decision-Making (MCDM) Framework, combining AHP and TOPSIS methods to automatically validate geospatial data in real time. The framework improved accuracy up to 92.5% and achieved an F1-score of 90.7%, outperforming conventional methods. This finding underscores blockchain's potential to ensure authenticity and transparency in spatial data, which provides a foundation for the image-based classification model developed in this research.

Additionally, Cahyo and Hindarto (2025) designed a Smart Contract Architecture for a Blockchain-Driven Multi-Criteria Decision Support System (DSS) dedicated to forest fire monitoring. Their work highlighted the weaknesses of centralized systems susceptible to data manipulation and introduced smart contracts that automatically record decision-making and risk evaluations. This demonstrates blockchain's strength in enhancing auditability and accountability in disaster management processes.

Lastly, Alrayes et al. (2024) proposed a Blockchain-Based Optimal Deep Learning (BIEODL-SDDC) model for disease detection in smart healthcare systems. The model combined image encryption with blockchain smart contracts to secure medical image transmission before classification using EfficientNet-B7. Methodologically, this research is relevant as it exemplifies how blockchain can be merged with deep learning to create a transparent and secure image-classification system, a principle adapted in this study for forest fire analysis.

*name of corresponding author

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In summary, previous research confirms the independent effectiveness of CNN and blockchain technologies. However, there remains an absence of studies that integrate both within a unified framework for forest fire classification that ensures accuracy, data security, and transparency. Therefore, this research introduces an integrated approach that combines ResNet-50 and VGG-16 with IPFS and smart contracts to form an auditable, replicable, and practical system for more reliable and intelligent forest fire detection.

METHOD

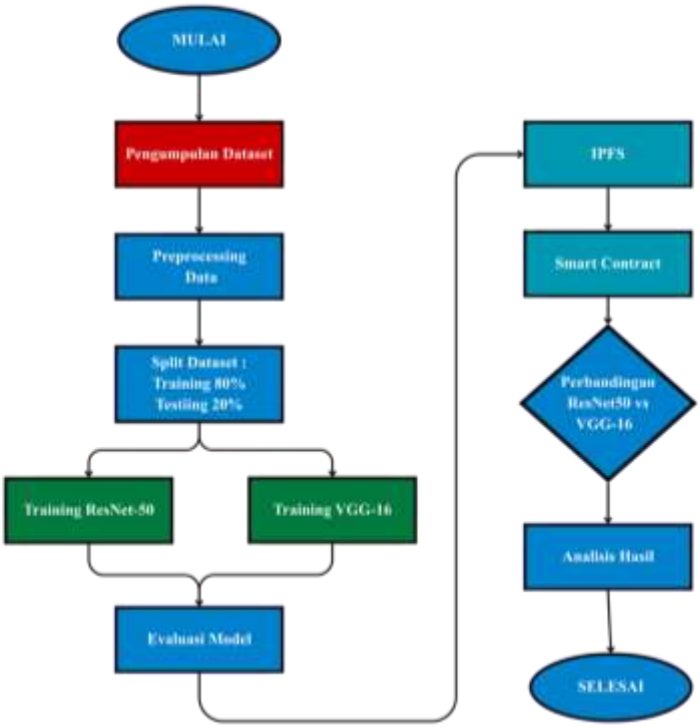

Fig.1 Proposed Research Method

Figure 1 illustrates the research method flow, which begins with the collection of forest fire image datasets consisting of two main categories, namely fire and non-fire. The dataset collection process was carried out by combining two main sources, namely local data and public data, in order to produce a more representative collection of data on actual forest fire conditions while also improving the model's generalization capabilities. Local data was collected from the Puncak region of Bogor, Indonesia, using drone cameras and smartphone cameras to obtain images in various lighting conditions, smoke density levels, and different vegetation variations. This collection yielded 500 local images, consisting of 250 forest fire images and 250 non-fire images, reflecting the visual characteristics typical of tropical forest fires in Indonesia. In addition, this study also used the public FIRE Dataset (Phylake1337). This public dataset contains thousands of fire and non-fire images from various regions and environmental conditions, thereby expanding the diversity of images used and strengthening the model's ability to recognize visual patterns of forest fires in various situations.

All data then goes through a preprocessing stage, including resizing, normalization, and data augmentation to improve image variation and quality before training. After that, the dataset is divided into two parts, namely 80% for training and 20% for testing to ensure a balance between the model learning process and performance validation. The next stage is training the CNN model using two popular architectures, namely ResNet-50 and VGG-16, each of which has different characteristics and network depths to detect visual patterns of forest fires.

After the training process was completed, model performance was evaluated using accuracy, precision, recall, and F1-score metrics to assess the classification effectiveness of each architecture. The model results and evaluation metrics were then uploaded to the InterPlanetary File System (IPFS) to ensure data security, integrity, and traceability through a decentralized content addressing-based storage system. Each uploaded file generates a unique Content Identifier (CID) that is recorded in a blockchain-based smart contract, ensuring that all experimental results are publicly verifiable and cannot be modified. This research process concludes with a comparative performance analysis of ResNet-50 and VGG-16, which aims to determine the best architecture for accurate, transparent, and replicable forest fire image classification.

*name of corresponding author

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ResNet-50

The ResNet-50 (Residual Network) architecture was used in this study because of its ability to overcome the vanishing gradient problem that often arises in deep neural networks. ResNet-50 was introduced by He et al. (2016) and is known for its skip connection or residual learning concept, an approach that allows information to pass through several layers without losing important features. Mathematically, ResNet does not directly learn the target function H(x), but rather learns the residual function F(x), which is defined as:

$$F(x) = H(x) - x \tag{1}$$

So the original function can be rewritten as:

$$H(x) = F(x) + x \tag{2}$$

where H(x) is the output of the residual block, F(x) is a non-linear transformation function of the input x, and x is an identity mapping that is passed directly. This approach helps the model retain information from the initial layers and speeds up the convergence process during training. The forward propagation process in the residual block is generally expressed as:

$$y = F(x, \{W_i\}) + x \tag{3}$$

where y is the residual block output, and $F(x, \{W_i\})$ is the result of a series of convolution operations, batch normalization, and the ReLU activation function with weight parameters W_i. If the input and output dimensions are different, a projection shortcut with 1×1 convolution is used, so that the equation becomes:

$$y = F(x, \{W_i\}) + W_s x \tag{4}$$

where W_s is a 1×1 convolution weight that serves to equalize the number of channels in the input and output.

In ResNet-50, each residual block consists of three convolution layers known as bottleneck blocks, with the mathematical form:

$$F(x) = W_3\, \sigma(\mathrm{BN}(W_2\, \sigma(\mathrm{BN}(W_1 x)))) \tag{5}$$

where $W_1 is\ a\ 1 \times 1\ convolution\ for\ dimension\ reduction, W_2$ is a 3×3 convolution for feature extraction, and W_3 where W_1 is a 1×1 convolution for dimension reduction, W_2 is a 3×3 convolution for feature extraction, and W_3 is a 1×1 convolution for channel restoration. σ represents the ReLU activation function, and BN is Batch Normalization, which serves to stabilize the activation distribution between layers.

In this study, ResNet-50 was trained using transfer learning with pretrained weights from ImageNet and fine-tuned on the final classification layer for two target classes, namely fire and non-fire (Dwiputra et al., 2023). The training process used the Adam optimizer, a learning rate of 0.0001, and a categorical cross-entropy loss function defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{6}$$

where C is the number of classes, y_i is the actual label, and $\hat{y}_i$ is the model's predicted probability. Model evaluation is performed using four main metrics: accuracy, precision, recall, and F1-score, which are mathematically expressed as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

Test results show that ResNet-50 is capable of achieving high accuracy with good training stability, particularly in detecting complex visual patterns such as burnt vegetation texture, fire color, and smoke density (Zhang et al.,

*name of corresponding author

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2023). Thus, ResNet-50 has proven to be superior in detecting forest fires through digital images and is suitable as a reference architecture in deep learning-based research and blockchain-integrated classification systems.

VGG-16

The VGG-16 (Visual Geometry Group) architecture is used as a comparison model to assess relative performance against ResNet-50. This model was developed by Simonyan and Zisserman (2014) and consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. Each convolutional layer uses a 3×3 kernel with a small stride and a Rectified Linear Unit (ReLU) activation function, which is mathematically expressed as:

$$f(x) = \max(0, x) \tag{11}$$

This function plays an important role in adding non-linearity to the network while accelerating the training process. Every two or three convolutional layers are followed by a max pooling layer to reduce the spatial dimensions of the features and reduce the computational load. Mathematically, the max pooling operation can be described as:

$$Y(i,j) = \max_{(m,n)\in R(i,j)} X(m,n) \tag{12}$$

where X(m,n) is the convolution result value, and R(i,j) is a fixed-size pooling window (usually 2×2). Meanwhile, the two-dimensional convolution operation on each layer can be written as:

$$Z(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot K(m,n) \tag{13}$$

where K(m,n) is the convolution kernel used to extract local features from fire images. This model uses transfer learning with pre-trained weights from ImageNet and is fine-tuned on the final classification layer to match the two target classes (fire and non-fire) (Kumar & Kumar, 2023).

The evaluation was performed using the same metrics as in ResNet-50, namely accuracy, precision, recall, and F1-score, to maintain consistency in comparing the performance between models. Based on the training and testing results, VGG-16 showed high stability and good generalization ability despite requiring longer computation time (Sharma et al., 2022). Its simple hierarchical structure allows for easier feature interpretation through feature visualization, helping researchers understand how visual patterns such as flames and smoke are identified by the model. This study reinforces the results of Hindarto et al. (2025), which show that VGG-16 can be integrated with blockchain-based systems to ensure data integrity and transparency of training results. Thus, despite being more computationally intensive, VGG-16 remains relevant for digital image-based forest fire detection systems, especially in contexts that require high model reliability and interpretability.

IPFS

The InterPlanetary File System (IPFS) is a decentralized peer-to-peer protocol and network designed to store and distribute digital data securely, efficiently, and without relying on a single server. IPFS replaces the location-based addressing concept in the HTTP protocol with a content-based addressing system, where each file is identified using a Content Identifier (CID) generated from a cryptographic hash function applied to the file's content. This approach enables data integrity verification because even the smallest change to a file will result in a different CID. Mathematically, content identification can be expressed as:

$$\mathrm{CID} = H(d) \tag{14}$$

where H is a hash function (e.g., SHA-256) and d is the data that is converted into a unique value. Data Structure and Storage Mechanism When a file is uploaded to IPFS, the data is divided into several small pieces called chunks with a fixed size (usually 256 KB). Each chunk is hashed independently to produce a unique identity, and all pieces are organized in a Merkle Directed Acyclic Graph (Merkle-DAG) structure. The relationship between chunks can be written as:

$$h_i = H(\mathrm{chunk}_i), h_{\mathrm{root}} = H(h_1 \parallel h_2 \parallel \ldots \parallel h_n) \tag{15}$$

where h_i is the hash of each chunk and h_{root} is the parent (root) hash that serves as the overall identity of the file. The Merkle-DAG structure allows IPFS to automatically deduplicate data, so that files with identical parts do

*name of corresponding author

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not need to be stored again. Data Distribution and Replication IPFS uses a Kademlia-based Distributed Hash Table (DHT) system to organize data storage and discovery between nodes on the network. In this mechanism, each node has a peer ID generated from its public hash function, and data searches are performed based on the XOR distance between nodes, defined as:

$$\text{dist}(a, b) = a \oplus \tag{16}$$

The smallest distance indicates the most relevant node storing the related chunk. This process ensures that data retrieval and distribution are fast, efficient, and resistant to node failure. Data Security and Integrity One of the main advantages of IPFS is its ability to verify data integrity by comparing the hash between the downloaded file and its original CID. Mathematically, the verification process can be described as:

$$H(\hat{d}) = \text{CID} \tag{17}$$

Where $\hat{d}$ is the downloaded data. If the hash result is identical to the original CID, then the data is declared authentic and has not been modified. With this system, IPFS provides a strong tamper-proof guarantee for all stored data.

RESULT

This section presents the results of implementing a forest fire image classification system that has been integrated with blockchain technology through IPFS and smart contracts. The test results focus on the performance of two CNN architectures, namely ResNet-50 and VGG-16, as well as validating the system integration using a Decentralized Application (DApp) built on the Ethereum network. An analysis was conducted to evaluate the accuracy of the model in recognizing forest fire images, as well as to assess the effectiveness of storing the model results on the blockchain, which guarantees data transparency and security. All experimental results, including evaluation metrics, environmental data, and training result files, were uploaded and verified in a decentralized manner through the minting mechanism on IPFS.

Fig.1 Insert To Ledger

Figure 1 shows the interface of the Forest Fire Detection System, which lets users upload images of fires and environmental information like latitude, longitude, temperature, and humidity. After the image is processed by either the ResNet-50 or VGG-16 model, the system displays performance results like accuracy, precision, recall,

*name of corresponding author

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and F1-score in a comparison chart. The system then shows the outcome of the analysis, and users can choose to record the results on the blockchain using MetaMask. Each time a record is added, there is a transaction fee and a unique hash that proves the record is permanently stored. The recorded results appear in the "Minted Records" section, showing the Content Identifier (CID) from IPFS, the location details, temperature, humidity, and the model used. This setup ensures accurate visual results and keeps all data and model outcomes safe, clear, and verifiable on the blockchain.

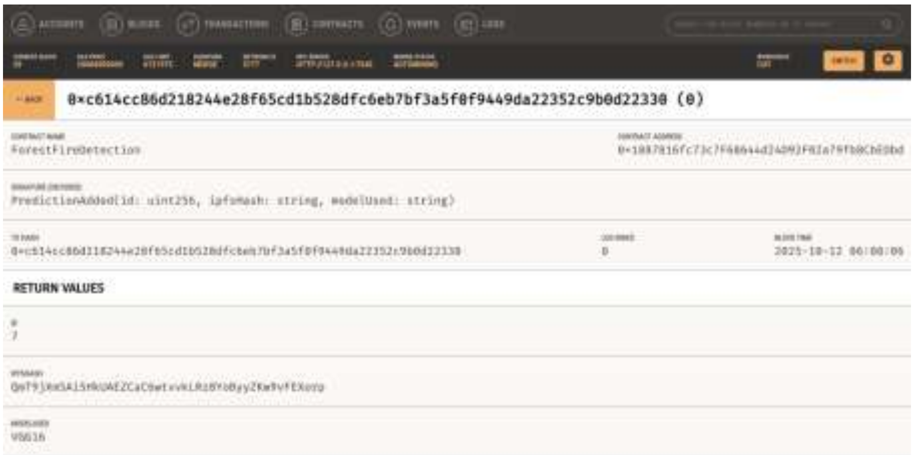

Fig.2 Transaction Record on Ganache Network

Figure 2 shows the Ganache interface, which functions as a local blockchain network for recording transactions from the ForestFireDetection smart contract. At the top, network information such as the current block number, gas price, and network ID connected to the local server via RPC is displayed. In the CONTRACTS panel, the deployed smart contract displays logs from the PredictionAdded event, which contains parameters such as data ID, IPFS hash, and the model used (VGG16). The RETURN VALUES section shows the results of the execution, confirming that the prediction data has been successfully stored permanently on the blockchain. Through this display, Ganache helps developers verify, monitor, and ensure that each prediction result is stored securely and transparently before being applied to the actual Ethereum network.

A. ResNet-50

Evaluation Metrics ResNet-50

Class	Precision	Recall	F1-Score	Support
0 (Non Fire)	0.85	0.93	0.89	151
1 (Fire)	0.68	0.48	0.56	48
Accuracy			0.82	199
Macro Avg	0.76	0.70	0.72	199
Weighted Avg	0.81	0.82	0.81	199

Fig.3 Evaluation Metrics of ResNet-50 Model

Figure 3 presents the evaluation results of the ResNet-50 model's performance in classifying forest fire images. As shown in the table, the model obtained an overall accuracy of 0.82, performing better in identifying non-fire images than fire ones. The precision and recall for the non-fire class were 0.85 and 0.93, respectively, demonstrating the model's strong consistency in detecting areas without fires. In contrast, for the fire class, the precision of 0.68 and recall of 0.48 reveal that the model still struggles to accurately recognize fire-containing images. Overall, the weighted average F1-score of 0.81 suggests that ResNet-50 maintains stable performance and serves as a solid foundation for further integration with blockchain and IPFS-based systems.

*name of corresponding author

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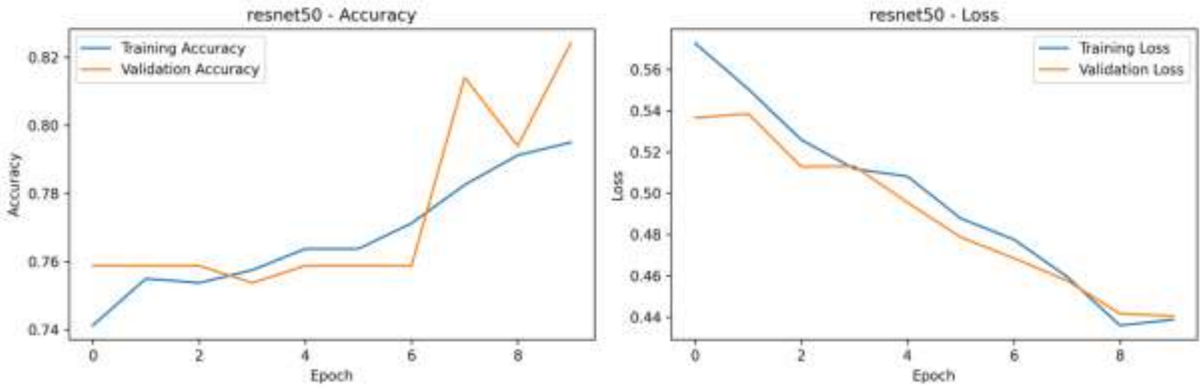

Fig.4 Training and Validation Accuracy and Loss of ResNet-50 Model

Figure 4 illustrates the training performance of the ResNet-50 model, displaying accuracy and loss values across multiple epochs. The graph on the left depicts an increase in training accuracy from approximately 0.74 to 0.79 by the final epoch, while validation accuracy follows a similar pattern, reaching a peak of about 0.82. Meanwhile, the graph on the right shows a steady decline in both training and validation loss, suggesting that the model learns effectively without experiencing major overfitting. The minimal gap between the two curves indicates strong generalization capability on the test dataset. Overall, these findings demonstrate that ResNet-50 achieves a well-balanced relationship between training and validation accuracy while maintaining efficient convergence during the learning phase.

B. VGG-16

Evaluation Metrics VGG-16

Class	Precision	Recall	F1-Score	Support
0 (Non Fire)	0.91	0.98	0.95	151
1 (Fire)	0.92	0.71	0.80	48
Accuracy			0.91	199
Macro Avg	0.92	0.84	0.87	199
Weighted Avg	0.91	0.91	0.91	199

Fig.5 Evaluation Metrics of VGG-16 Model

Figure 5 presents the evaluation results of the VGG-16 model in classifying forest fire images. The model achieved an overall accuracy of 0.91, demonstrating excellent capability in identifying non-fire classes, with precision and recall values of 0.91 and 0.98, respectively. For the fire class, a precision of 0.92 and recall of 0.71 indicate that the model effectively detects fire regions, although minor prediction errors remain. The macro average F1-score of 0.87 and the weighted average F1-score of 0.91 reflect the model's robustness when handling imbalanced datasets. Overall, these outcomes confirm that VGG-16 surpasses ResNet-50 in performance, particularly in maintaining an optimal balance between precision and sensitivity across both classes.

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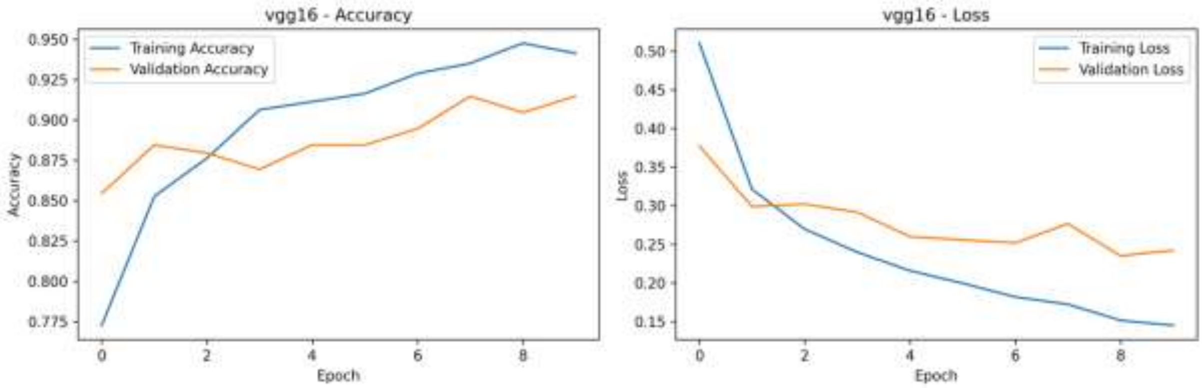

Fig.6 Training and Validation Accuracy and Loss of VGG-16 Model

Figure 6 illustrates the training performance of the VGG-16 model based on accuracy and loss trends over multiple epochs. The left graph shows a steady rise in training accuracy from 0.77 to approximately 0.95, while validation accuracy increases consistently to about 0.91. On the right, the graph indicates a sharp decline in training loss from 0.50 to roughly 0.14, accompanied by a reduction in validation loss to around 0.23. The minimal gap between both curves demonstrates that the model generalizes well and avoids significant overfitting. Overall, these findings show that VGG-16 achieves more stable and efficient training compared to ResNet-50, exhibiting faster convergence and consistent validation performance.

C. Comparison

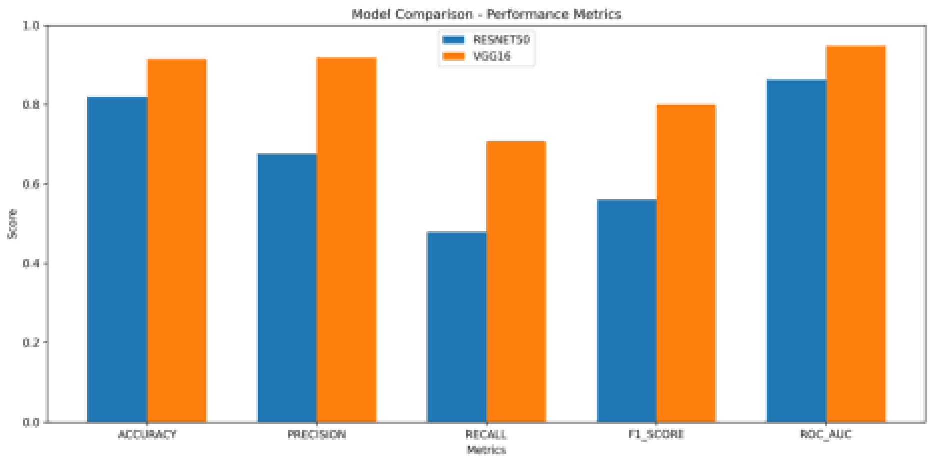

Fig.7 Training and Validation Accuracy and Loss of VGG-16 Model

Figure 7 compares the performance of the ResNet-50 and VGG-16 models across key evaluation metrics accuracy, precision, recall, F1-score, and ROC-AUC. It is evident that VGG-16 consistently outperforms ResNet-50 in all metrics, achieving accuracy and precision values of approximately 0.91 and 0.92. While both models perform satisfactorily, VGG-16 shows a noticeable improvement, particularly in recall and F1-score, indicating its stronger ability to detect fire images with higher sensitivity and balance. The ROC-AUC value of nearly 0.97 further confirms the model's high classification accuracy and reliability. Overall, these findings demonstrate that the VGG-16 architecture is more effective than ResNet-50 in forest fire image classification, maintaining an optimal equilibrium between precision and sensitivity.

DISCUSSIONS

The results indicate that the VGG-16 model surpasses ResNet-50 in forest fire image classification, achieving an accuracy of 0.91, precision of 0.92, and an F1-score of 0.87. This superiority arises from VGG-16's multi-layer convolutional structure, which enables the extraction of intricate visual features such as vegetation textures, smoke density, and flame regions. Conversely, despite ResNet-50's deeper network design, it tends to suffer from reduced recall due to its higher complexity and the need for more extensive data to reach optimal convergence. Integrating model training outputs with IPFS and blockchain-based smart contracts adds an extra layer of security, ensuring that each prediction result is permanently and transparently stored using a unique Content Identifier (CID). This

*name of corresponding author

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mechanism enhances reproducibility and reliability since every model and dataset can be independently verified without risk of data alteration.

When compared with previous work by Dwiputra et al. (2023), which focused solely on CNN-based forest fire detection, this study advances the concept by incorporating decentralization through blockchain integration. It also aligns with the framework of Hindarto et al. (2025), who applied smart contracts in geospatial disaster mitigation, but differs in application focus by emphasizing data security and traceability in image classification outcomes. Nevertheless, this research faces certain limitations, including a relatively small local dataset that may constrain the model's generalization across varying geographic and lighting conditions. Additionally, only two CNN architectures were evaluated, excluding lightweight alternatives such as MobileNet or EfficientNet, which could offer better efficiency for real-time use. Future improvements may involve integrating IoT-based sensor data for real-time monitoring and refining smart contracts to autonomously manage a broader range of prediction parameters on the blockchain network.

CONCLUSION

This study successfully integrated Blockchain and Neural Network technologies into a forest fire image classification framework by comparing two well-known architectures, ResNet-50 and VGG-16. The experimental results showed that VGG-16 significantly outperformed ResNet-50, achieving an accuracy of 0.91 and an F1-score of 0.87, while ResNet-50 reached an accuracy of 0.82 and an F1-score of 0.72. The integration of the InterPlanetary File System (IPFS) with blockchain-based smart contracts ensured that all model outputs, predictions, and parameters were securely, transparently, and immutably stored. The main contribution of this research lies in the creation of an end-to-end framework that not only enhances model performance but also maintains the integrity and traceability of experimental data in a decentralized manner. Although the proposed method demonstrates strong performance, it still has limitations such as a relatively small dataset and the use of only two CNN architectures without exploring more lightweight models suitable for real-time field deployment. Future research is recommended to expand the dataset across diverse geographic and atmospheric conditions and to evaluate efficient models such as MobileNet or EfficientNet. Further development could also integrate IoT-based sensor data and automate smart contract reporting to achieve adaptive, real-time forest fire detection. Overall, this research contributes significantly to the development of an intelligent, secure, transparent, and replicable forest fire detection system, while opening opportunities for broader blockchain applications in AI-based disaster mitigation.

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