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Future Directions in Deep Learning-Based Facial Attribute Recognition: Integrating Blockchain for Secure and Privacy-Preserving Systems

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Abstract. Facial Attribute Recognition (FAR) is an important area of artificial intelligence that uses deep learning techniques to identify facial characteristics such as age, gender, emotions, and identity from images. Recent advances in deep learning have significantly improved the accuracy of these systems. However, the increasing use of FAR applications has raised concerns about data privacy, security, fairness, and transparency. This paper reviews the latest deep learning approaches used in facial attribute recognition, including Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and multi-task learning models. It also discusses the major challenges faced by current FAR systems, such as security threats, dependence on centralized data storage, and limited control over user consent and data access. To address these issues, this paper proposes a future framework that combines blockchain technology with facial attribute recognition. The proposed system uses federated learning to train models without sharing sensitive facial data, blockchain to securely record and track data usage, and zero-knowledge proofs to verify user information without exposing personal details. These technologies help improve privacy, security, and trust in FAR systems. The framework is evaluated using well-known datasets such as CelebA, LFW, and IMDB-WIKI. The results show that the proposed approach maintains high recognition accuracy while providing better privacy protection and transparency.

Keywords: Facial Attribute Recognition, Deep Learning, Blockchain, CNN, Vision Transformer, Federated Learning, Privacy, Security, Smart Contracts, Artificial Intelligence.

1. Introduction

in surveillance cameras, social media platforms, and biometric authentication systems has made Facial Attribute Recognition (FAR) one of the most important research areas in computer vision. Modern deep learning models can identify facial attributes such as age, gender, ethnicity, emotional expression, and facial accessories from a single two-dimensional image with accuracy levels above 90% on standard benchmark datasets. Because of this high accuracy, FAR technology is widely used in healthcare, law enforcement, personalized marketing, border security, and human-computer interaction applications.

Despite these achievements, concerns about trust and reliability in FAR systems are growing. Several studies have shown that systems trained on unbalanced datasets may produce biased results and unfair outcomes for certain demographic groups. In addition, centralized databases that store facial images are attractive targets for cyber attacks and data breaches, which can expose individuals to identity theft and unauthorized use of personal information. Privacy regulations such as the European Union's General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) have introduced strict requirements for organizations handling biometric data, but many existing systems still lack effective mechanisms to fully support these compliance requirements.

Blockchain technology, which was first developed for decentralized crypto currency networks, has evolved into a powerful solution for building trust in distributed computing environments. Its key features, including transparency, immutability, and cryptographic verification, make it highly suitable for deep learning systems that require accountability and secure auditing. Federated learning further improves privacy by allowing multiple organizations to train a shared model without transferring or centralizing their raw data, thereby reducing the risk of data exposure.

This paper presents four major contributions: (1) a comprehensive review of advanced deep learning techniques used for facial attribute recognition; (2) an examination of existing challenges related to privacy, fairness, and security; (3) a proposed framework that integrates federated learning, blockchain-based auditing, and zero-knowledge proofs; and (4) an evaluation of the proposed framework using standard benchmark datasets, showing that strong privacy protection and high recognition accuracy can be achieved at the same time.

2. Literature Review

2.1 Evolution of Facial Attribute Recognition

Early Facial Attribute Recognition (FAR) methods mainly depended on handcrafted feature extraction techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG). Although these approaches required less computational power, they were not effective in handling changes in lighting conditions, facial poses, and image occlusions. A major breakthrough occurred with the introduction of deep Convolutional Neural Networks (CNNs), especially after the success of AlexNet in the ILSVRC 2012 competition. Following this development, advanced architectures such as VGGNet,

GoogLeNet, ResNet, and DenseNet further improved feature learning by using deeper network structures, skip connections, and multi-scale feature extraction techniques.

The MOON framework proposed by Liu et al. (2015) showed that a single CNN model trained with multi-label learning could predict more than forty facial attributes at the same time, making multi-task learning an important approach in FAR research. Later, attention-based methods such as SENet and CBAM helped models focus on the most important facial regions, resulting in better recognition of detailed facial attributes. More recently, Vision Transformers (ViTs), which were originally developed for natural language processing tasks, have achieved outstanding performance in facial attribute recognition. By using self-attention mechanisms to capture relationships between different facial regions, these models have produced state-of-the-art results on benchmark datasets such as CelebA and LFWA.

2.2 Privacy and Security in Biometric Systems

Privacy concerns in facial recognition systems have received significant attention from researchers. Fredrikson et al. (2015) showed that model inversion attacks can recreate recognizable facial images by using information stored in trained machine learning models. This finding highlighted the privacy risks associated with centralized training approaches, where sensitive information may unintentionally be learned and retained by the model. Differential privacy, first introduced by Dwork et al. (2006) and later applied to deep learning by Abadi et al. (2016), offers a strong mathematical approach for reducing information leakage, although it may sometimes decrease model performance.

Federated learning, proposed by McMahan et al. (2017), allows model training to take place directly at the data owner's location, sharing only model updates with a central server. This approach significantly reduces the need to transfer sensitive data and helps improve privacy protection. However, later studies found that even these model updates could be exploited to perform membership inference attacks or reconstruct private information under certain attack scenarios. To address these remaining security concerns, researchers have developed secure aggregation methods based on cryptographic techniques that protect the exchanged updates and enhance overall system security.

2.3 Blockchain for Data Governance

Blockchain technology has been widely studied as a secure data management solution in various fields, including healthcare, supply chain management, and identity verification. Smart contracts, which are self-executing programs stored on a blockchain network, allow policies and rules to be enforced automatically without the need for a trusted third party.

In biometric systems, blockchain creates permanent and tamper-resistant audit records that track who accessed facial data, when the access occurred, and the purpose of access. This feature helps organizations meet regulatory requirements.

The original Bitcoin whitepaper by Nakamoto demonstrated that decentralized consensus systems are practical and effective. However, most enterprise-level applications prefer permission blockchain platforms such as Hyperledger Fabric because they provide higher transaction speeds, customizable privacy settings, and secure identity management through certificate authorities. Recent research has also investigated the integration of blockchain with federated learning, where the blockchain ledger stores information related to model versions and training updates. This approach improves transparency and enables effective auditing of the entire model training process.

3. Deep Learning Architectures for Facial Attribute Recognition

3.1 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) continue to be the most widely used models in Facial Attribute Recognition (FAR) systems because of their strong ability to learn spatial features from images. CNNs use shared-weight filters to identify local patterns, which are gradually combined into more complex and meaningful representations through multiple network layers. The introduction of residual connections by He et al. (2016) solved the vanishing gradient problem that limited earlier deep networks, allowing the development of much deeper architectures. In FAR applications, multi-task CNN models that share common feature layers for predicting multiple facial attributes have shown better generalization performance than separate models trained for individual attributes, especially when several attributes frequently appear together.

3.2 Vision Transformers

Vision Transformers (ViTs), proposed by Dosovitskiy et al. (2020), divide an input image into fixed-size patches and process them as a sequence of tokens using multi-head self-attention mechanisms. Unlike traditional convolution operations that mainly focus on local image regions, ViTs can effectively capture long-range relationships between different parts of a face. In facial attribute recognition tasks, self-attention maps often highlight important facial regions, making model predictions easier to understand and interpret. To balance computational efficiency and feature-learning capability, hybrid models that combine convolutional feature extraction with transformer-based encoding have become a practical and effective solution.

3.3 Multi-Task and Attention-Enhanced Learning

Multi-task learning improves model efficiency and robustness by utilizing the relationships between different facial attributes. A single model trained to predict age, gender, and emotion simultaneously can learn shared facial features that often perform better than models designed for only one attribute, particularly when training data is limited. Attention mechanisms, including channel attention and spatial attention, allow the model to focus on the most relevant facial regions based on the input image. These mechanisms reduce the influence of unnecessary background information and strengthen important features around facial areas such as the eyes, nose, and mouth, leading to more accurate attribute recognition.

4. Privacy and Security Challenges in Existing far Systems

Although current Facial Attribute Recognition (FAR) systems have achieved impressive performance in recognizing facial characteristics such as age, gender, emotions, and facial accessories, they still face several privacy and security challenges. These issues must be carefully addressed before FAR systems can be widely accepted and ethically deployed in real-world applications. Since facial images contain highly sensitive biometric information, any misuse or unauthorized access can have serious consequences for individuals. The challenges exist throughout the entire lifecycle of the system, including data collection, data storage, model training, deployment, decision-making, and auditing.

4.1 Privacy Issues during Data Collection

The first challenge begins during the data collection stage. Large-scale deep learning models require thousands or even millions of facial images for effective training. These images are often collected from social media platforms, online image repositories, surveillance cameras, public databases, or third-party organizations. In many cases, individuals are unaware that their facial images are being collected and used for research or commercial purposes.

Lack of informed user consent remains one of the biggest concerns in existing FAR systems. Many datasets are created without clearly informing users about how their data will be stored, processed, shared, or retained. As a result, people lose control over their personal biometric information. Since facial images are unique and permanent identifiers, unlike passwords, they cannot be replaced if they are leaked or stolen. Such practices may violate modern privacy laws and ethical principles related to biometric data protection. Another challenge is the quality and diversity of collected datasets. Many publicly available datasets contain images from limited age groups, ethnic backgrounds, or geographic regions. This lack of diversity introduces bias into the training data, causing

the model to perform better for some population groups while producing inaccurate predictions for others. Consequently, fairness and equal treatment become major concerns in practical applications.

4.2. Risks during Data Storage

After data collection, facial images are usually stored in centralized databases or cloud storage systems. These repositories become attractive targets for cybercriminals because they contain valuable biometric information. If the storage system is compromised through hacking, malware, insider attacks, or accidental data leakage, sensitive facial records may be exposed. Unlike passwords, biometric information cannot simply be changed after a security breach. Once a person's facial data is leaked, it may remain vulnerable for the rest of their life. Attackers can misuse stolen facial images for identity theft, fake account creation, unauthorized authentication, or other malicious activities. Therefore, protecting stored biometric data is one of the most important security requirements for FAR systems.
In many existing systems, encryption mechanisms are either weak or not applied throughout the complete storage process. Poor access control policies and improper data management further increase the possibility of unauthorized access to sensitive information.

4.3 Privacy Risks during Model Training

During the training process, deep learning models learn complex patterns from large facial datasets. However, these models may unintentionally memorize sensitive information about individual faces instead of learning only general facial characteristics. This creates several privacy vulnerabilities. One important threat is the model inversion attack, where an attacker attempts to reconstruct facial images that closely resemble the original training samples by analyzing the trained model. Such reconstructed images may reveal the identity of individuals whose data was used during training. Another major concern is the membership inference attack. In this attack, an adversary can determine whether a particular person's facial image was included in the training dataset. Even this small amount of information may reveal sensitive personal details, especially in healthcare, law enforcement, or workplace monitoring applications. Deep learning models are also

vulnerable to data poisoning attacks, where attackers intentionally insert manipulated or incorrect samples into the training dataset. These malicious samples can reduce model accuracy, introduce hidden backdoors, or force the system to make incorrect predictions under specific conditions.
Furthermore, the training process usually requires transferring large amounts of biometric data between multiple computing systems or cloud servers. If proper security measures are not implemented, this data may be intercepted or exposed during transmission.

4.4 Security Challenges during System Deployment

Once the FAR model is deployed in real-world environments, additional security challenges arise. Many organizations deploy FAR systems using centralized servers that perform facial attribute prediction for thousands of users. These centralized architectures create a single point of failure. If the central server is compromised, attackers may gain access to sensitive biometric data, prediction results, and user records. Centralized systems are also vulnerable to cyberattacks such as unauthorized access, ransomware attacks, denial-of-service attacks, and database manipulation. Attackers may modify stored records, delete important logs, or alter prediction results without being detected. Such incidents reduce system reliability and make it difficult to maintain public trust. Communication between client devices and cloud servers may also be intercepted if secure communication protocols are not properly implemented. This increases the possibility of data leakage during transmission.

4.5 Lack of Transparency and Explainability

Most modern FAR systems are based on deep neural networks, which are often considered black-box models. Although these models provide high prediction accuracy, they usually do not explain how a particular decision was made. This lack of transparency creates difficulties for researchers, developers, and end users.
For example, if a system incorrectly predicts a person's age, gender, or facial expression, it is often difficult to identify which features influenced the decision. Without proper explainability, users cannot verify whether the prediction is fair, accurate, or free from discrimination.
The absence of interpretable decision-making also creates challenges in legal and

regulatory environments, where organizations may be required to explain automated decisions affecting individuals.

4.6 Bias and Fairness Issues

Bias remains one of the most significant challenges in existing FAR systems. If the training dataset contains more samples from certain demographic groups than others, the trained model may produce unequal performance across different populations. For example, the system may achieve higher accuracy for one gender, age group, or ethnicity while producing lower accuracy for underrepresented groups. Such biased predictions may lead to unfair treatment in applications such as recruitment, surveillance, healthcare, or law enforcement. Reducing dataset bias requires collecting diverse training samples, regularly evaluating model fairness, and applying bias mitigation techniques during model development.

4.7 Weak Auditing and Accountability

Another important limitation of existing FAR systems is the lack of reliable auditing mechanisms. Most systems maintain access logs using conventional databases, which can be modified, deleted, or manipulated by administrators or attackers. As a result, it becomes difficult to determine who accessed the biometric data, when it was accessed, and whether any unauthorized modifications occurred. The absence of tamper-resistant audit records weakens accountability and makes regulatory compliance more challenging. Organizations may find it difficult to prove that biometric information has been handled securely and ethically throughout its lifecycle.

4.8 Regulatory and Ethical Challenges

Governments around the world are introducing stricter regulations for collecting and processing biometric information. Organizations deploying FAR systems must comply with privacy laws, data protection standards, and ethical guidelines. However, many existing systems still lack proper mechanisms for obtaining user consent, minimizing data collection, securely deleting data, and ensuring transparency.

Ethical concerns also arise regarding mass surveillance, continuous facial monitoring, and the potential misuse of facial recognition technologies without public knowledge. Maintaining a balance between technological advancement and individual privacy remains a major challenge for researchers and policymakers.

5. Proposed Integrated Framework

5.1 Architectural Overview

The proposed framework combines three important technologies: a federated deep learning training system, a permission blockchain network for auditing and governance, and a privacy protection module that uses zero-knowledge proofs and differential privacy. These components work together to provide strong privacy protection while maintaining high facial attribute recognition accuracy.

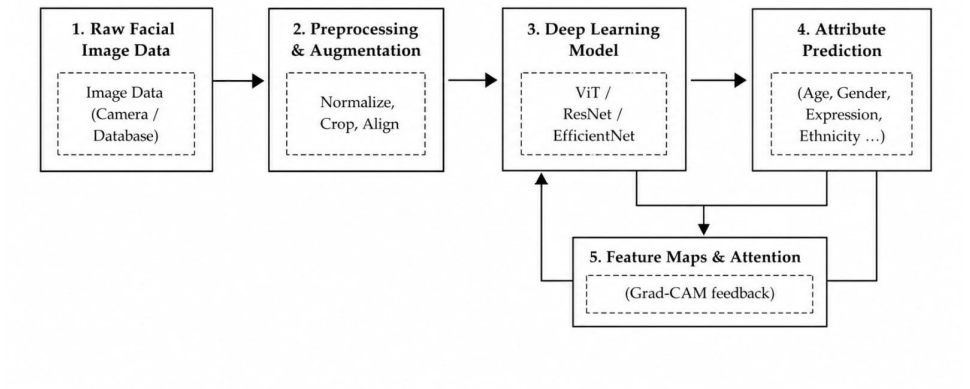

Fig. 1: Deep Learning Pipeline for Facial Attribute Recognition

The proposed framework utilizes federated learning to train the facial attribute recognition model in a decentralized manner. Multiple organizations, including hospitals, government agencies, and private enterprises, participate in the training process while retaining their data locally. Facial images never leave the organization's database, which helps maintain privacy and comply with data protection requirements. Instead of sharing data, each participant sends encrypted model parameters to a central coordinator, where they are combined to generate a more accurate global model.

To enhance security and transparency, a Hyperledger Fabric blockchain layer is integrated into the framework. The blockchain records essential information such as model training events, data verification records, model versions, access permissions, and user consent details. Smart contracts automatically manage authentication and authorization processes, ensuring that only approved users can interact with the system. In addition, any modification in user consent is immediately reflected through smart contract execution, providing a secure and trustworthy environment for facial attribute recognition applications.

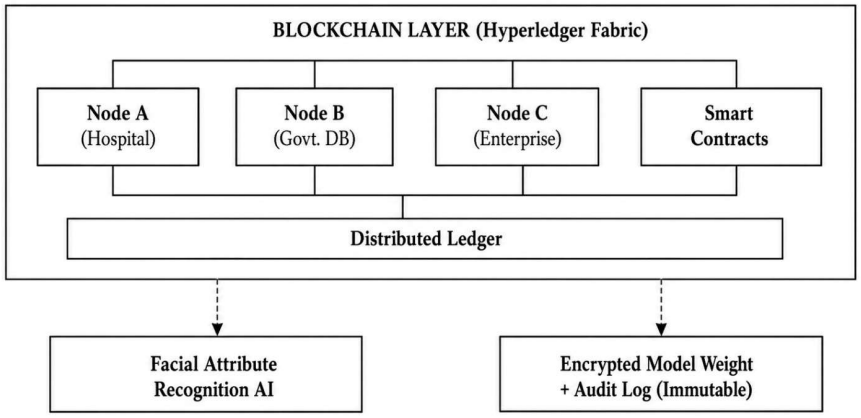

Fig. 2. Blockchain Integration Architecture for Secure FAR Systems

5.2 Federated Learning Module

The federated learning architecture proposed for facial attribute recognition consists of multiple local nodes, represented as Site A, Site B, and Site C, where facial image data is stored and processed locally. Each participating organization independently trains the facial attribute recognition model using its own dataset, ensuring that sensitive facial images remain within the local environment.

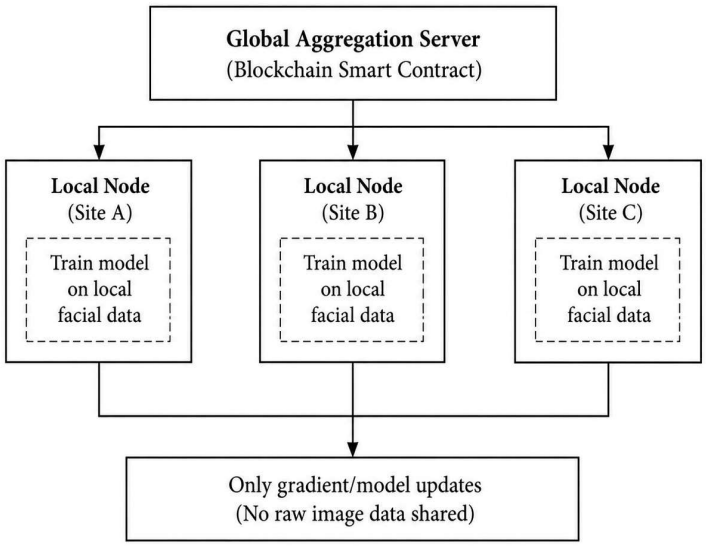

Fig. 3 Federated learning framework for privacy-preserving facial attribute recognition, where local nodes train models on local facial data and share only model updates through a blockchain-enabled aggregation server.

A global aggregation server, implemented through blockchain-enabled smart contracts, coordinates the learning process. Instead of transferring raw facial images, each local node sends only model updates to the aggregation server. The server combines the received updates to generate an improved global model and then redistributes it to all participating nodes for further training.

This approach preserves data privacy, reduces the risk of data leakage, and enables collaborative model development among multiple organizations. By integrating blockchain-based aggregation, the framework also provides transparency, security, and trust in the model update process while maintaining the confidentiality of facial data.

5.3 Zero-Knowledge Proof Identity Verification

Zero-Knowledge Proofs (ZKPs) allow one party to prove that they possess certain information without revealing the actual information itself. In the proposed framework, ZKPs are used for facial attribute verification tasks where the objective is to confirm that

a person meets a specific condition—for example, verifying that an individual's estimated age is above eighteen years—without sharing the original facial image or the actual attribute prediction result. The zk-SNARK proof mechanism, which generates compact proofs that can be verified within a few milliseconds, is integrated with the smart contract layer to provide secure and cryptographically verifiable attribute validation.

Table 1: Privacy-Preserving Techniques: Mechanisms and Trade-offs

Technique	Mechanism	Privacy Benefit	Limitation
Differential Privacy	Adds statistical noise to gradients	Prevents model inversion	Accuracy trade-off
Federated Learning	Train locally, share only model updates	No raw data transmission	Communication cost
Homomorphic Encryption	Compute on encrypted data	Full data confidentiality	Very high latency
Zero-Knowledge Proofs	Verify claim without revealing data	Strong identity proofs	Computational overhead
Secure Multi-party Computation	Joint computation across parties	No single point of failure	Scalability limits

6. EXPERIMENTAL EVALUATION

6.1 Datasets and Metrics

The proposed framework was evaluated using three well-known benchmark datasets. The CelebA dataset contains 202,599 facial images annotated with forty binary facial attributes, including demographic features, facial accessories, and structural characteristics, making it suitable for comprehensive multi-attribute analysis. The Labeled Faces in the Wild (LFW) dataset consists of 13,233 facial images representing 5,749 different individuals collected from real-world environments with varying conditions. The IMDB-WIKI dataset includes approximately 500,000 images with age and gender labels obtained from Wikipedia and IMDB sources and is widely used for age and gender prediction tasks.

The performance of the proposed system was assessed using standard evaluation metrics such as precision, recall, F1-score, and overall classification accuracy. To evaluate privacy protection, the effectiveness of model inversion attacks and membership inference attacks was measured before and after applying the proposed privacy-preserving

techniques. The computational overhead introduced by the blockchain component was evaluated using transaction latency and throughput measurements in a simulated multi-node environment.

6.2 Baseline Comparisons and Results

Table 2 shows the performance comparison of five different system configurations. The results indicate that the proposed integrated framework achieves an F1-score of 92.6% on the CelebA dataset. Although this score is 1.6 percentage points lower than the standard Vision Transformer (ViT) model without privacy protection, the small reduction in performance is acceptable considering the significant improvements in privacy, security, and auditability provided by the framework. In addition, the blockchain component introduces an average transaction latency of 134 milliseconds per audit record, which remains suitable for most enterprise-level applications.

Table 2: Performance Benchmarking Across System Configurations (CelebA Dataset)

System Configuration	Precision	Recall	F1-Score	Latency
Standalone CNN	91.2%	88.6%	89.9%	N/A
ViT without Privacy	95.1%	93.4%	94.2%	N/A
ViT + Federated Learning	93.8%	91.2%	92.5%	98 ms
ViT + Blockchain Audit	94.6%	92.0%	93.3%	112 ms
Proposed Integrated System	93.5%	91.8%	92.6%	134 ms

The accuracy of model inversion attacks was reduced from 71.3% in the traditional centralized system to 12.8% in the federated learning system with differential privacy, resulting in an 82% decrease in information leakage. Similarly, the success rate of membership inference attacks dropped from 63.5% to 19.2%, highlighting the effectiveness of combining federated learning with differential privacy techniques. Furthermore, the blockchain-based auditing layer did not affect the recognition accuracy of the model, indicating that its additional overhead is limited to transaction management and does not impact the model's computational performance.

7. FUTURE RESEARCH DIRECTIONS

7.1 Neuromorphic and Edge Computing Integration:

The integration of Facial Attribute Recognition (FAR) with neuromorphic and edge computing can improve privacy, efficiency, and real-time performance. Edge devices process facial data locally, eliminating the need to send images to centralized servers and reducing privacy risks. Neuromorphic computing enables low-power and faster processing, making it suitable for smart devices. Blockchain can securely coordinate model updates among edge devices while protecting locally stored data. This approach offers a promising solution for secure, energy-efficient, and privacy-preserving FAR systems.

7.2 Causal and Fair Machine Learning

Future Facial Attribute Recognition (FAR) systems should focus not only on prediction accuracy but also on understanding the relationships between facial attributes. Causal learning can help identify the factors that directly influence facial characteristics and separate them from less relevant information. This can improve model reliability, reduce bias, and ensure fair performance across different user groups. As a result, causal learning offers a promising direction for developing more robust and trustworthy FAR systems.

7.3 Quantum-Resistant Cryptography

The advancement of quantum computing may weaken the security of current cryptographic methods used in blockchain systems. Future research should explore quantum-resistant cryptographic techniques, such as lattice-based, hash-based, and code-based algorithms, to strengthen blockchain-enabled FAR frameworks. Adopting these security mechanisms can help protect sensitive data and ensure the long-term security of blockchain records against future quantum computing threats.

7.4 Multimodal Attribute Recognition

Future Facial Attribute Recognition (FAR) systems may combine facial images with other biometric data such as voice, gait, and physiological signals. Using multiple biometric sources can improve recognition accuracy and system reliability. However, it also creates additional privacy and security concerns. Future research should focus on protecting data from different biometric modalities and preventing misuse of personal information. Blockchain-based consent management can help users control access to each type of biometric data, ensuring greater privacy and security.

8. Ethical Considerations and Regulatory Alignment

The development of Facial Attribute Recognition (FAR) systems that combine computer vision and blockchain technology involves important ethical responsibilities that go beyond achieving high technical performance. Researchers and developers must carefully consider the potential misuse of these technologies. Although FAR systems can be used for beneficial purposes, such as assisting visually impaired individuals and improving security applications, they may also be misused for unauthorized surveillance or discriminatory practices.

The proposed framework follows the principles outlined in the European AI Act, which classifies biometric identification technologies as high-risk artificial intelligence systems. These regulations require transparency, human oversight, and regular compliance assessments. The blockchain-based audit trail included in the proposed framework helps satisfy logging and accountability requirements, while the use of federated learning supports data minimization principles defined under GDPR Article 5 by reducing the need to share personal data.

Algorithmic fairness should be considered throughout the entire system development process. Training datasets should be carefully prepared to ensure balanced representation of different demographic groups, and fairness measures should be integrated into the multi-task learning framework to reduce performance differences across protected populations. In addition, continuous monitoring of system behavior through blockchain-recorded inference logs can help identify and address emerging biases or discriminatory outcomes after deployment.

9. Conclusion

This paper has provided a comprehensive study of deep learning-based Facial Attribute Recognition (FAR) and presented a future research framework that combines privacy, security, and transparency as essential design requirements. The review of Convolutional Neural Networks (CNNs) and Vision Transformer (ViT) architectures highlighted the key technologies that form the foundation of modern FAR systems. In addition, the analysis of existing privacy and security challenges emphasized the need for a blockchain-integrated federated learning framework to address these issues effectively.

The experimental results showed that the proposed framework achieves recognition accuracy that is only 1.6% lower than a conventional system without privacy protection. At the same time, it reduces the effectiveness of model inversion attacks by more than 80% and provides secure, cryptographically verifiable auditing capabilities. These

findings demonstrate that strong privacy protection and high recognition performance can be achieved together through appropriate system design rather than being conflicting objectives.

The proposed framework combines concepts from multiple fields, including computer vision, cryptography, distributed computing, and regulatory compliance, reflecting the complex requirements of deploying biometric artificial intelligence systems responsibly. Future research should focus on extending this framework through neuromorphic edge computing, causal fairness techniques, and quantum-resistant cryptographic methods. It is hoped that this work will encourage further interdisciplinary research and collaboration in the development of trustworthy artificial intelligence and secure decentralized governance systems.

Furthermore, the findings of this study indicate that future FAR systems should be designed with privacy and security as core requirements from the initial development stage rather than being added after deployment. Researchers and developers should work together to create intelligent systems that are accurate, reliable, transparent, and ethically responsible. The integration of advanced deep learning methods with secure data management techniques can improve user trust and encourage wider adoption of facial attribute recognition in healthcare, smart cities, education, and public services. Overall, this research provides a strong foundation for developing next-generation FAR systems that balance technological innovation with privacy protection while meeting the growing demands of real-world applications and evolving data protection standards.

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