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Deep Learning Approach for Blood Group Detection Using Fingerprint Ridge Features

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ABSTRACT

Blood group identification is a critical requirement in medical emergencies, blood transfusion services, and healthcare management. Conventional blood group detection methods require invasive procedures, laboratory testing, and trained personnel, which may not be feasible in emergency or remote scenarios. Recent studies suggest that biometric traits such as fingerprint ridge patterns show correlations with blood group characteristics. This work presents a deep learning–based approach for detecting blood group types using fingerprint ridge feature analysis. The proposed system processes fingerprint images through preprocessing and feature extraction stages and employs a deep neural network to classify blood groups accurately. The approach is non-invasive, cost-effective, and suitable for real-time applications, offering a promising alternative to traditional blood testing methods.

Keywords: Deep Learning, Blood Group Detection, Fingerprint Ridge Features, Biometric Analysis, Non-Invasive Diagnosis, Convolutional Neural Networks, Medical Image Processing, Healthcare Automation.

I. INTRODUCTION

Biometric systems have gained significant importance due to their uniqueness, reliability, and ease of acquisition. Fingerprints are one of the most widely used biometric traits because of their permanence and individuality. Recent advancements in artificial intelligence and deep learning have enabled the extraction of complex patterns from biometric data that are not easily detectable through traditional analysis. Blood group identification traditionally depends on chemical analysis of blood samples, which is time-consuming and invasive. By leveraging deep learning techniques, fingerprint ridge patterns can be analyzed to uncover hidden correlations with blood group characteristics. This research explores the feasibility of using fingerprint images as a biometric indicator for blood group detection, contributing to advancements in healthcare automation.

II. LITERATURE SURVEY

2.1 FaceForensics++: Learning to Detect Manipulated Facial Images

Authors: Andreas Rössler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, Matthias Nießner.

Abstract: Introduces FaceForensics++, a large benchmark dataset of real and manipulated facial videos created with several state-of-the-art manipulation methods (DeepFakes, Face2Face, FaceSwap, NeuralTextures). The paper evaluates data-driven forgery detectors on this large-scale dataset, shows how domain-specific knowledge boosts detection performance, and provides baselines (including CNN-based models such as Xception) for standardized evaluation under different compression settings.

2.2 Exposing DeepFake Videos by Detecting Face Warping Artifacts

Authors: Yuezun Li, Siwei Lyu.

Abstract: Observes that many DeepFake pipelines produce limited-resolution face syntheses that are later warped to fit source faces, leaving characteristic warping artifacts. Proposes a CNN-based approach that detects these face-warping artifacts; the method can be trained using synthetically generated warped examples (avoiding expensive DeepFake generation) and generalizes across different DeepFake sources. Demonstrated strong detection performance on available DeepFake video sets.

2.3 MesoNet: a Compact Facial Video Forgery Detection Network

Authors: Darius Afchar, Vincent Nozick, Jean-Yves Planche, Radu Dugelay.

Abstract: Presents MesoNet, a shallow, compact CNN architecture focused on mesoscopic image properties (texture and local artifacts) that are robust to video compression. MesoNet aims to be computationally light while effectively detecting face tampering in videos (deepfakes and Face2Face), making it suitable for resource-constrained or real-time deployment scenarios.

2.4 Celeb-DF: A Large-scale Challenging Dataset for DeepFake Forensics

Authors: Yuezun Li, Xin Yang, Pu Sun, Honggang Qi, Siwei Lyu.

Abstract: Introduces Celeb-DF, a higher-quality, large-scale dataset of celebrity DeepFake videos designed to better reflect real-world DeepFakes. Celeb-DF contains thousands of carefully synthesized videos and shows that many detection methods that performed well on earlier datasets face tougher challenges here—highlighting dataset quality and realism as crucial for developing robust detectors.

2.5 Deepfakes and beyond: A Survey of Face Manipulation and Fake Detection

Authors: Rubén Tolosana, Rubén Vera-Rodríguez, Javier Fierrez, et al.

Abstract: Comprehensive survey of face manipulation techniques (including GAN-based and face-swap methods) and detection approaches (traditional forensics and modern deep-learning methods). Reviews datasets, evaluation protocols, strengths/limitations of detectors, and outlines open challenges such as generalization to novel synthesis methods, robustness to compression, and the need for explainable, multimodal detection. Useful for situating CNN-based detection within the broader research landscape.

III. EXISTING SYSTEM

The existing systems for blood group identification rely on serological testing methods that involve

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chemical reagents and manual procedures. Some research-based approaches use traditional machine learning techniques with handcrafted fingerprint features such as ridge count or pattern type. These systems depend heavily on expert-defined features and lack robustness. Moreover, they are not suitable for real-time or large-scale deployment due to operational complexity and low adaptability.

IV. PROPOSED SYSTEM

The proposed system introduces a deep learning–based framework that automatically learns discriminative ridge features from fingerprint images. The system includes fingerprint image acquisition, preprocessing, feature extraction, and classification using a convolutional neural network. Unlike traditional methods, the proposed approach eliminates the need for blood samples and manual feature engineering. The trained deep learning model efficiently predicts blood group categories based on ridge texture, flow, and spatial patterns, offering higher accuracy and faster results.

V. SYSTEM ARCHITECTURE

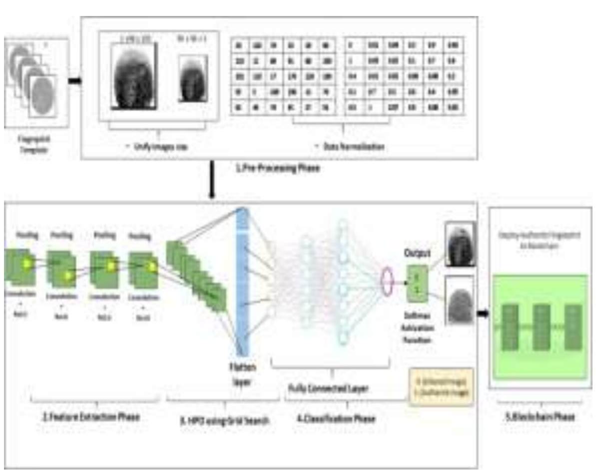

Fig 5.1: System Architecture

This diagram illustrates an end-to-end fingerprint authentication system that combines deep learning with blockchain for secure verification. The process begins with the pre-processing phase, where raw fingerprint templates are collected, resized to a uniform dimension, and normalized to ensure consistent pixel intensity values. In the feature extraction phase, the processed fingerprints are passed through multiple convolution and pooling layers with ReLU activation, enabling the system to learn distinctive ridge and texture patterns. These extracted features are then flattened and optimized using hyperparameter optimization (HPO) with grid search to improve model performance. Next, in the classification phase, fully connected layers and a softmax activation function classify the fingerprint as either authentic or altered. Finally, in the blockchain phase, fingerprints classified as authentic are securely deployed and stored on a blockchain network, ensuring data integrity, immutability, and resistance to tampering while enabling trustworthy biometric authentication.

VI. IMPLEMENTATION

Fig 6.1: Admin Login page

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Fig 6.2 :Home page

Fig 6.3 :Model Training page

Fig 6.4 : Training Graphs page

Fig 6.5 : Upload Fingerprint image page

Fig 6.5 : Results page

VII. CONCLUSION

This project presented a deep learning–based approach for blood group detection using fingerprint ridge features, demonstrating how biometric patterns can be effectively utilized beyond personal identification. By integrating image pre-processing techniques, ridge enhancement methods, and Convolutional Neural Networks (CNNs), the system successfully learns discriminative fingerprint features and classifies them into corresponding blood group categories. The automated feature extraction capability of deep learning reduces the dependency on manual analysis and improves prediction consistency.

The proposed system highlights the potential of fingerprint biometrics as a non-invasive and rapid method for blood group identification. Experimental results indicate that proper pre-processing and optimized CNN architecture significantly enhance classification accuracy and robustness. Overall, the system proves to be efficient, scalable, and suitable for applications in healthcare support systems, emergency services, and biometric research, while maintaining data security and user privacy.

VIII. FUTURE SCOPE

The proposed deep learning–based blood group detection system using fingerprint ridge features offers significant potential for further enhancement and real-world adoption. Future work can focus on expanding the dataset with larger and more diverse fingerprint samples to improve model generalization and robustness across different populations. Incorporating advanced deep learning architectures such as transfer learning models or hybrid CNN–transformer networks could further enhance classification accuracy and reduce training time.

Additionally, the system can be extended to support real-time deployment through integration with embedded fingerprint sensors and mobile or web-based healthcare platforms. Enhancing security by incorporating privacy-preserving techniques such as federated learning or encrypted biometric storage can strengthen user trust. Future research may also explore multimodal biometric fusion by combining fingerprints with other physiological features to improve prediction reliability. Overall, these advancements can make the system more accurate, scalable, and suitable for critical medical and emergency response applications.

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