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DETECTING BLOOD GROUP THROUGH FINGERPRINT ANALYSIS

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***Abstract*— A fingerprint's pattern is among the most reliable and distinctive characteristics for identifying individuals, remaining consistent throughout a person's lifetime. In different situations, especially within legal proceedings, the evidence of fingerprints is well respected. The specific minutiae pattern of every individual is unmatched, with the chances of similarity being extremely low, almost one in sixty-four thousand million. This uniqueness is even valid for identical duplet. Ridge patterns on fingerprints are formed before birth and stay constant throughout a person's life, making them a dependable trait for individual recognition. This article proposes a technique using comparison of certain feature patterns obtained through fingerprints for personal identification systems. Fingerprint data has also been investigated for its potential use in identifying an individual's blood group. During fingerprint matching, ridge frequency is measured and spatial attributes are extracted with the help of a Gabor filter for this very purpose. Therefore, blood group can be identified from fingerprint analysis.**

keywords— ***Biometrics, Blood group identification, Fingerprint analysis, Gabor filters, Pattern recognition, Ridge frequency***

I.INTRODUCTION

Deep learning, in the form of artificial intelligence, specifically Convolutional Neural Networks (CNNs), has been demonstrated to be a superior method for learning intricate features from image data. Given a large dataset of fingerprint images annotated with their corresponding blood types, CNNs are able to identify subtle and distinctive traits linked to each blood group. The greatest advantage of deep learning is that it can automatically classify and extract features with excellent precision, thereby minimizing the level of manual processing. This characteristic makes it highly suitable for creating a reliable fingerprint-based system for detecting blood group. The technology has excellent real-world application in the clinical and emergency settings. In a remote or resource-constrained setting where lab facilities are unavailable, the technology can provide an immediate and consistent method of determining blood group from a mere fingerprint scanner. Also, in the event of mass casualty or natural catastrophe, emergency medical first responders may employ this system to immediately.

ascertain an individual's blood type so that timely and possibly life-giving treatment can be provided The integration of artificial intelligence with biometric systems in healthcare highlights how advanced technologies can effectively contribute to solving real-world medical challenges.

II.LITERATURE REVIEW

Jain et al [1]. provided an extensive overview of fingerprint- based biometric systems and how they are used for identity verification applications. The authors discussed the most crucial aspects of fingerprint recognition systems, which are the technology for acquiring fingerprints, techniques for extracting representative features, and algorithms for pattern matching. The authors categorized fingerprint features into minutiae-based and ridgebased methods and described how each allows reliable individual identification. Moreover, the research solved key problems like quality image reduction, partial fingerprint images, and spoofing attacks. Their study is a definitive guide for researchers that aim to improve fingerprint recognition systems and outsmart current limitations with better algorithms and preprocessing methods. Lütjens et al. [2] presented an extensive review of the application of deep learning techniques in medical diagnosis, and wonderful advances have been observed in medical imaging, diagnosis, and predictive modeling. The authors stressed the significance of Convolutional Neural Networks (CNNs) for processing complex medical data such as X-rays, MRIs, and microscopic images by extracting implicit features automatically that are often ignored by conventional methods. Their research also discussed some of the key issues that were data scarcity, interpretability of models, and ethics of deep learning usage in

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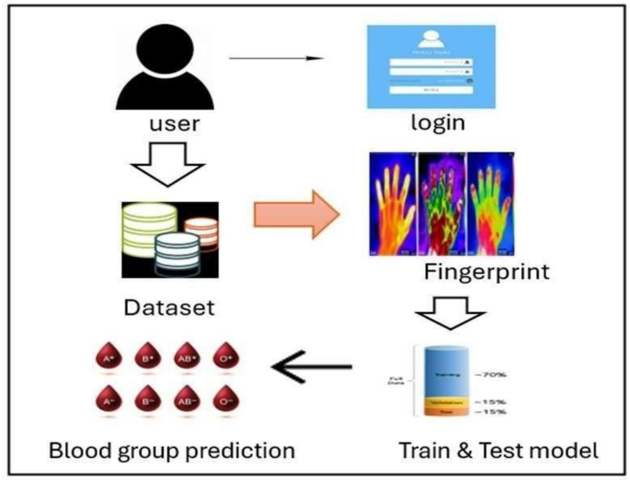
medicine. Specifically, the survey discussed using deep learning models on non-conventional biomedical inputs, i.e., biometric signals, and how the latter can be utilized to infer internal health parameters—e.g., blood group— from external features like fingerprints. The current paper is the foundation for developing AI-based systems using fingerprint patterns in medicine for diagnosis. Bansal and Rajput [3] conducted statistical research exploring the relationship between fingerprint patterns and ABO blood groups. The researchers crosstabulated an array of fingerprints of individuals whose blood type was known to establish correlations between shared patterns on fingerprints— arches, whorls, and loops—and certain blood groups. They proved through statistical tests strong correlations that supported the evidence that some patterns on the fingerprint are more common in certain blood groups. While this study did not use deep learning methods, it is sound biological evidence that supports the hypothesis that genetic blood-type information can be encoded into dermatoglyphic patterns. This work paves the way for the use of AI and deep learning methods for the automation and improvement of blood group prediction from fingerprints and prompts future interdisciplinary work in biomedical informatics Nguyen et al. [4] examined the application of Convolutional Neural Networks (CNNs) in discovering patterns on various biometric modalities like iris scans, facial images, and fingerprints. The study refers to the superior ability of CNNs in identifying fine-grained and subtle patterns from image-based biological data compared to traditional machine learning techniques. Through comparative analysis, the authors established that CNNs deliver more accuracy and generalization biometric information classification, including fingerprint. Furthermore, they explored the possibility of CNNs not just for identity verification but also for ascertaining deeper biological features like predicting personal characteristics like blood type when trained on appropriately labeled databases. This paper is a good technical foundation for using deep learning models to advanced biometric systems.

III. METHODOLOGY

A. SYSTEM ARCHITECTURE



user initiates the process by logging into the system. This triggers access to a dataset containing fingerprint images along with their corresponding blood group information. The system then utilizes a train and test model, likely CNN algorithm, to analyze the user's fingerprint. Based on the patterns identified in the fingerprint and the knowledge learned from the training data, the system predicts

Login: An authentication module ensuring only authorized individuals access the system. It secures user data and system functionality.

Dataset: A meticulously curated collection of fingerprint images, each precisely labeled with the corresponding individual's blood group. The dataset is separated into three segments: one for training the model, another for validating it during development, and the last for final testing.

Fingerprint: The biometric input. This represents the captured image of the user's fingerprint, which serves as the primary feature for blood group prediction.

Train & Test Model:

Training (70% of Dataset): The phase where the Convolutional Neural Network (CNN) learns to extract distinctive patterns from fingerprint images and correlate them with specific blood groups. The CNN adjusts its internal parameters (weights, biases) to minimize prediction errors based on this labeled data. Validation (15% of Dataset): Used during training to fine-tune model hyperparameters and prevent overfitting. It provides an unbiased evaluation of model performance on unseen data before final testing. Testing (15% of Dataset): The final evaluation phase. The fully trained CNN's performance is assessed on a completely independent set of fingerprint images it has never encountered, providing a realistic measure of its generalization ability and accuracy.

Blood Group Prediction: The trained CNN processes a new, unseen fingerprint image and outputs its inferred blood group (e.g., A+, O-, B+).

Data Acquisition Module:

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This module handles the capture or input of fingerprint images. When we upload fingerprint from the dataset image preprocessing takes place.

Feature Extraction Module:

Minutiae Extraction: Identifying and extracting the unique minutiae points (ridge endings and bifurcations) of the fingerprint.

Ridge Frequency Assessment:Determining the ridges' frequency in the fingerprint.

Spatial Feature Extraction using Gabor Filter: Using Gabor filters for extracting spatial features associated with the patterns of ridges.

Model Training Module:

Utilize the training set for training the model, the tuning of hyperparameters by using the validation set.

We use CNN to train the model which analyze the fingerprints patterns.

Model Evaluation Module:

Test the model using a separate validation dataset to assess its accuracy

$$Z^{(l)} = \sigma(W^{(l)} * Z^{(l-1)} + b^{(l)}), \quad \text{for } l = 1 \text{ to } L$$

where:

- $Z^{(0)} = F$
- $W^{(l)}, b^{(l)}$ are weights and biases of layer l
- σ is the activation function (ReLU or softmax)

5. Output Prediction:

$$\hat{Y} = f_{\text{CNN}}(F) = \text{softmax}(Z^{(L)})$$

6. Loss Function (Categorical Cross-Entropy):

$$\mathcal{L}(Y, \hat{Y}) = -\sum_{i=1}^{k} Y_i \log(\hat{Y}_i)$$

7. Model Optimization:

the user's blood group. The final output is the predicted blood group.

User: The individual whose blood group is to be predicted. They initiate the process by providing their fingerprint.

It uses evaluation metrics like accuracy, precision.

Based on the fingerprint feature extraction blood group is determined.

and reliability in predicting blood groups.

B. ALGORITHM

1. Image Preprocessing and Feature Extraction:

$$I' = \frac{1}{255} \cdot \text{Resize}(\text{Grayscale}(I), (h, w))$$

2. Gabor Filter Application:

$$F = \sum_{\theta=0}^{\pi} \sum_{\lambda} G_{\theta,\lambda} * I'$$

Where * denotes convolution.

3. Dataset Formation:

$$X = \{F_1, F_2, ..., F_n\}, \quad Y = \{y_1, y_2, ..., y_n\}$$

4. CNN Forward Pass:

Fig 2: Login Page

In Fig 1, it shows the home page of the application which contains two tabs: *Home* and *User Login*, with *Home* being active. Fig 2, shows the login screen of a deep learning-based system for blood group detection using fingerprints. Users must enter a username and password to access the system.

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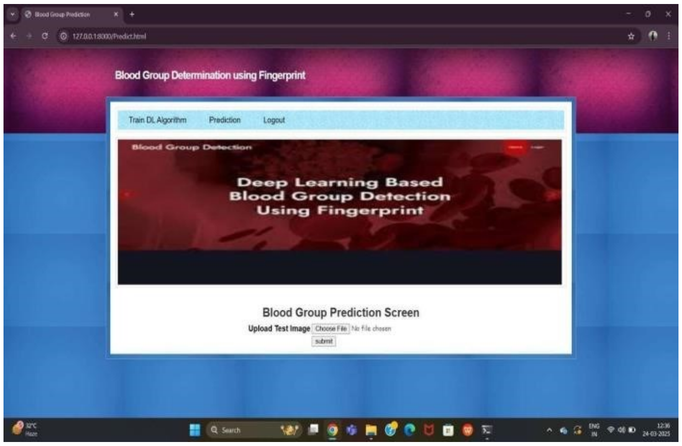

$$\theta \leftarrow \theta - \eta \cdot \nabla_{\theta}\mathcal{L}$$

where θ are model parameters, η is the learning rate.

8. Accuracy Metric:

Fig 3:Prediction Screen

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \times 100\%$$

IV.RESULTS

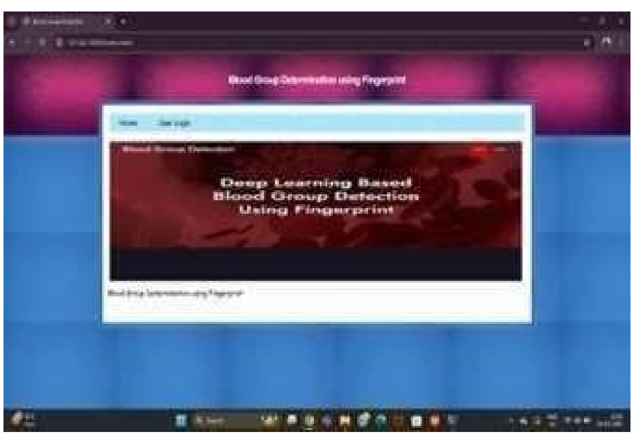

Fig 1: Home Page

In Fig 3 the screen allows users to upload a fingerprint image to predict blood group using a trained deep learning model. Fig 4 shows the process of selecting a fingerprint image from the dataset for blood group prediction. The selected image will be

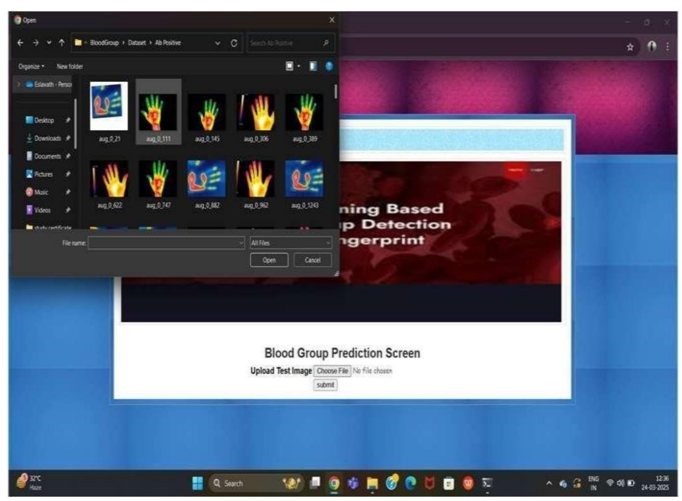

Fig 4:Prediction Screen

VII. REFERENCES

analyzed by the deep learning model to determine the blood group.

Fig 6: Prediction Result

V. CONCLUSION

The project *"Deep Learning Based Blood Group Detection Using Fingerprint"* presents an innovative, non-invasive method for identifying an individual's blood group using biometric data. Fingerprints, with their unique and unchanging ridge patterns, serve as highly reliable identifiers—so distinct that even identical twins do not share the same prints. This research goes beyond traditional identification by exploring the potential of fingerprints to reveal additional personal information, such as blood type. Through deep learning and advanced pattern analysis, the study demonstrates that subtle features within fingerprint ridges can be leveraged for medical insights. This approach not only enhances biometric identification but also opens new possibilities in healthcare diagnostics, emphasizing the untapped potential of fingerprint data.

VI. FUTURE SCOPE

The proposed system offers a number of prospects for potential development and application in real life in the future. They are one of the most necessary, namely its application in medical systems, where it will be possible to immediately identify blood groups in hospitals and emergency medical situations, thereby making it possible to perform faster medical interventions. Improved accuracy and generalizability would result from training the model from larger and more diverse fingerprint-blood group databases. The system would also find application in multi- parameter prediction where the biometric data would be applied to predict other health-based traits such as genetic blends or disease markers. In addition, utilization of the model by mobile applications or IoTbased biometric devices could potentially enhance handheld and remote blood grouping identification, particularly for groups of people in underdeveloped or rural areas. Furthermore, the technology can be used in sophisticated biometric security systems with medical identification data incorporated in fingerprint identification for enhanced security and access to customized medicine.

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