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BLOOD GROUP CLASSIFICATION FROM FINGERPRINTS USING A CUSTOM CNN APPROACH

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Abstract: Blood group determination plays a vital role in medical emergencies, blood transfusions, forensic identification, and organ transplantation. Conventional methods require physical samples and laboratory testing. This paper proposes a non-invasive and contactless approach using biometric fingerprints analyzed through a custom Convolutional Neural Network (CNN) designed from scratch. Unlike previous works, no pre-trained models or data augmentation techniques were used, ensuring a raw-data-centric model. The model achieved an overall classification accuracy of 91% across the eight major blood groups, highlighting its promise as a rapid, cost-effective, and scalable blood group prediction system [5][6].

Index Terms **- Blood Group Detection, Fingerprint Recognition, Convolutional Neural Network, Deep Learning, Biometrics, Classification, Custom CNN.**

I. INTRODUCTION

Blood group classification is a critical component of medical procedures, including emergency care, surgeries, transfusions, and organ transplants. Traditional blood typing methods, although accurate, are invasive and require laboratory infrastructure and expert handling, which can delay treatment in urgent or resource-limited settings.

To address these challenges, there is a growing interest in developing non-invasive, rapid, and cost-effective alternatives. Biometric technologies, particularly fingerprint analysis, offer a promising solution due to the uniqueness, stability, and ease of acquisition of fingerprint patterns. Recent studies have also indicated potential correlations between fingerprint ridge patterns and blood group types [1][2].

In this study, we propose a fingerprint-based blood group detection system using a deep learning model built entirely from scratch. Unlike previous works that rely on transfer learning or pre-trained models [3][4], our approach employs a custom-designed Convolutional Neural Network (CNN) trained on raw fingerprint data without any data augmentation. This ensures the model's performance reflects real-world applicability without artificial enhancements.

The main contributions of this work include:

- Development of a custom CNN architecture tailored for fingerprint image analysis.
- Training on un augmented raw fingerprint data to maintain data authenticity.
- Achieving over 90% classification accuracy across all eight major blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−).

Our approach demonstrates a scalable, efficient, and fully contactless method for blood group prediction, with potential for real-time use in mobile and remote healthcare environments.

II. LITERATURE REVIEW

Multiple approaches have been explored in the literature linking fingerprint analysis with blood group identification:

- Roy et al. [1] examined the ridge patterns in fingerprints to find correlations with blood groups.
- Ritu et al. [2] applied classical image processing on biometric traits for ABO and Rh factor prediction.
- Kumar et al. [3] experimented with transfer learning using ResNet50, obtaining ~94% accuracy.
- Nair et al. [4] explored biometric traits for predicting genetic characteristics using neural networks.
- Verma [5] presented a deep learning pipeline for multimodal biometric systems.

Most previous studies either relied on limited datasets, lacked generalization, or used pretrained deep learning models, raising questions about model dependency and overfitting. Our study is among the first to design a CNN architecture from scratch, evaluate on real-world data, and avoid any data augmentation techniques, thus assessing the model's performance in a raw-data environment.

III. METHODOLOGY

A. Dataset Collection

Fingerprint images of over 8000 individuals were collected with labelled blood group information. The original dataset showed a class imbalance (as shown in *Figure 1*), which was later equalized (as shown in *Figure 2*) for fair training. The dataset included all eight major blood groups and ensured diversity in age, gender, and skin texture [6].

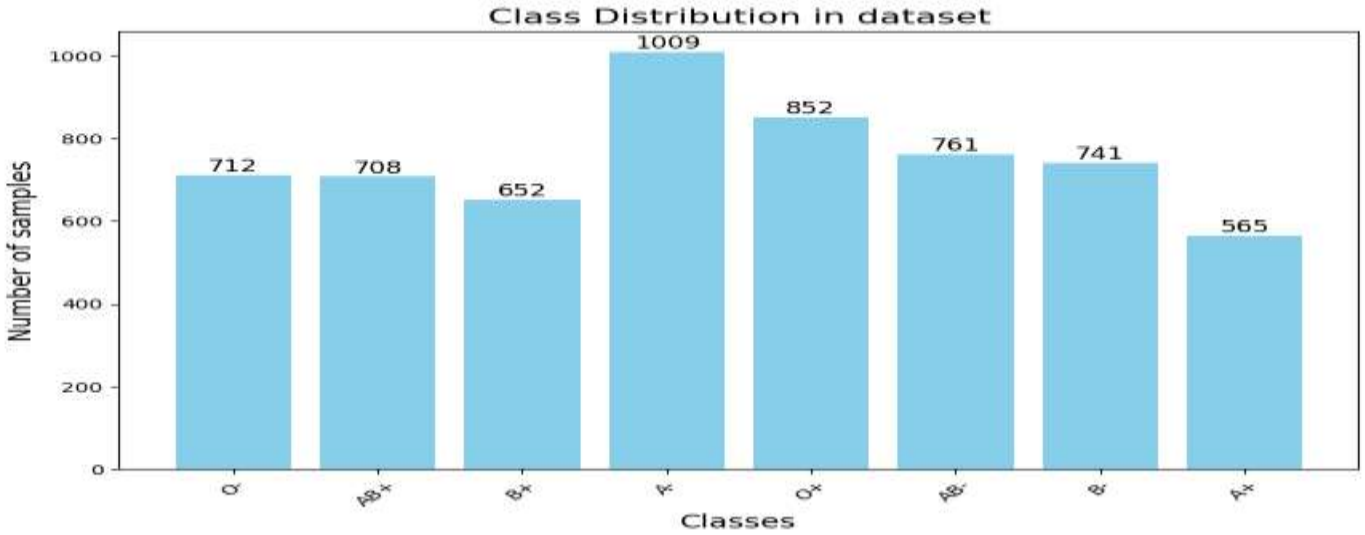

Figure 1: Initial class-wise distribution of the fingerprint dataset

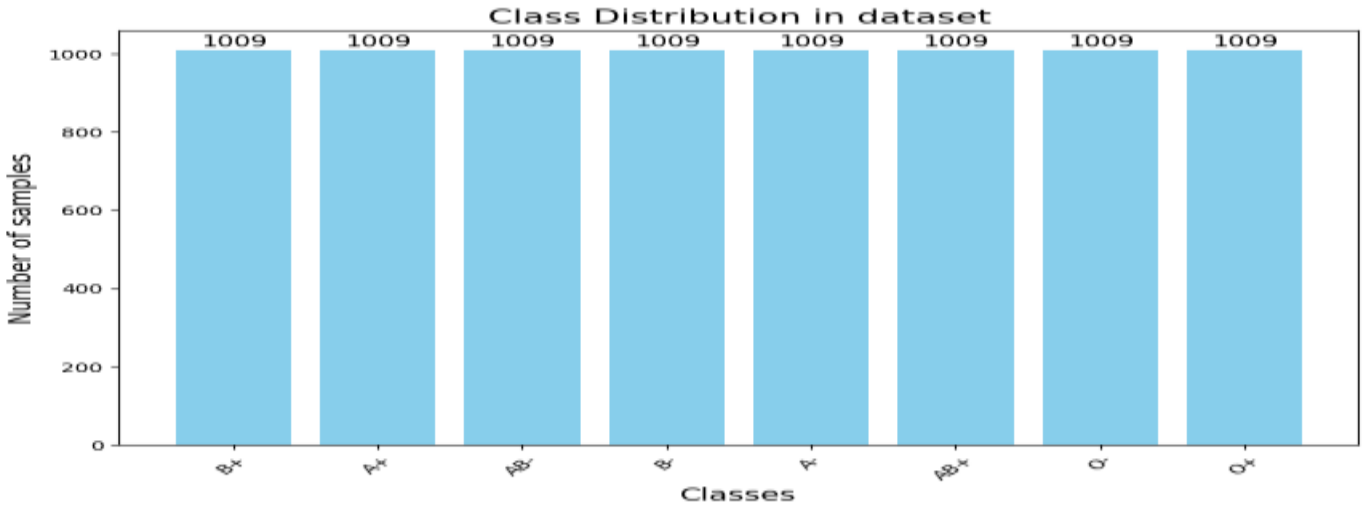

Figure 2: Class-wise distribution after applying oversampling and under sampling

B. Preprocessing

- All fingerprint images were resized to 64x64 pixels.
- Normalization was applied to scale pixel values between 0 and 1.
- No data augmentation or image enhancement was performed to preserve authenticity [6].

C. CNN Model Architecture

We designed the CNN from scratch using **TensorFlow-Keras**. The architecture includes six convolutional layers with increasing filters, ReLU activation, max-pooling, and dropout layers to prevent overfitting (as shown in *Figure 3*) [5].

```
def model():
    model = tf.keras.models.Sequential([
        tf.keras.layers.Conv2D(32, (3, 3), activation='relu', padding='same', input_shape = (64, 64, 3)),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.Dropout(0.3),

        tf.keras.layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.Dropout(0.4),

        tf.keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.Dropout(0.4),

        tf.keras.layers.Conv2D(256, (3, 3), activation='relu', padding='same'),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.Dropout(0.4),

        tf.keras.layers.Conv2D(512, (3, 3), activation='relu', padding='same'),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.Dropout(0.5),

        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(1024, activation = 'relu'),
        tf.keras.layers.Dropout(0.5),

        tf.keras.layers.Dense(len(class_names), activation='softmax')
    ])

    model.compile(optimizer = 'Adam',
                  loss = 'sparse_categorical_crossentropy',
                  metrics = ['accuracy'])
    return model

model = model()
```

Figure 3: Architecture of the custom CNN model used for fingerprint-based blood group classification.

D. Model Training

- Optimizer: Adam
- Loss Function: Sparse Categorical Cross entropy
- Epochs: 50
- Metrics: Accuracy

The model was trained on 80% of the dataset and validated on the remaining 20%.

IV. RESULTS AND DISCUSSION

A. Accuracy and Confusion Matrix

The model achieved a classification accuracy of 91%. Most blood groups had F1-scores above 0.90, with slight dips for rare classes such as AB− and O+ due to limited ridge pattern variation [6].

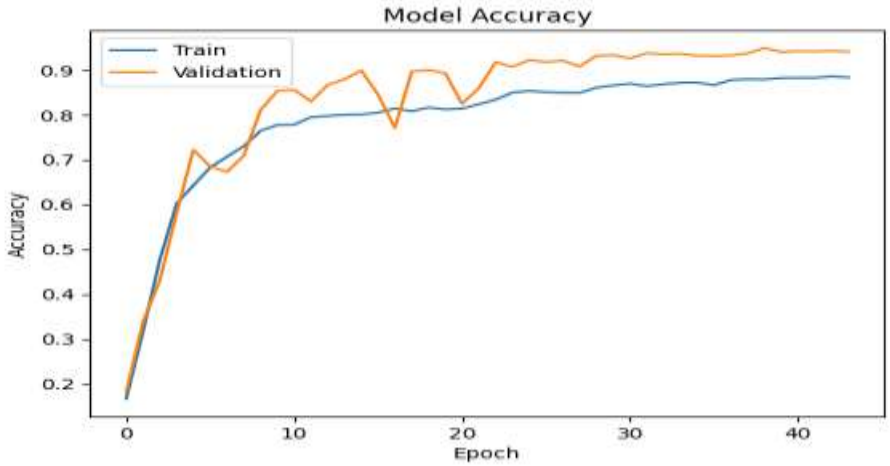

Figure 4: Training vs Validation Accuracy across epochs

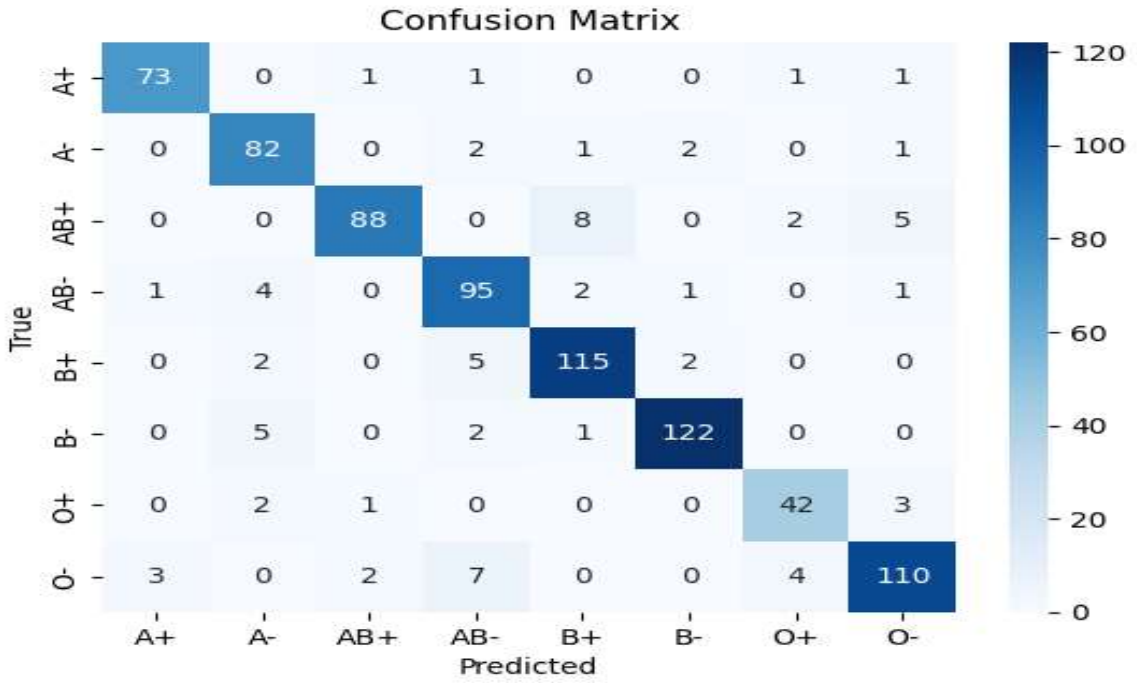

Figure 5: Confusion Matrix showing performance across 8 classes

B. Precision, Recall, and F1-Score

Detailed metrics show high consistency, with an average precision and recall of > 0.90 across most classes.

Classification Report:

	precision	recall	f1-score	support
A+	0.95	0.95	0.95	77
A-	0.86	0.93	0.90	88
AB+	0.96	0.85	0.90	103
AB-	0.85	0.91	0.88	104
B+	0.91	0.93	0.92	124
B-	0.96	0.94	0.95	130
O+	0.86	0.88	0.87	48
O-	0.91	0.87	0.89	126
accuracy			0.91	800
macro avg	0.91	0.91	0.91	800
weighted avg	0.91	0.91	0.91	800

Figure 6: Classification report of Precision, Recall, and F1-scores

C. Observations

- The model performed well on raw fingerprint inputs.
- Minimal preprocessing makes the system suitable for edge or mobile deployment [6][8].
- AB− and O+ classes showed slightly lower performance, warranting further research.

V. ADVANTAGES AND LIMITATIONS

Advantages:

- Non-invasive and contactless method.
- Fast and cost-effective.
- No dependency on pre-trained models.
- High portability for field deployments.

Limitations:

- Results might improve further with data augmentation.
- The dataset was balanced artificially — real-world distribution is inherently skewed.
- Requires a high-quality fingerprint scanner.
- Ethical concerns regarding biometric data storage must be addressed [8].

VI. CONCLUSION AND FUTURE SCOPE

This study presents a CNN-based system for fingerprint-based blood group prediction with minimal preprocessing and no reliance on pretrained models. The approach demonstrates potential for deployment in medical diagnostics, especially in rural or emergency settings.

Future Directions:

- Testing on real-world imbalanced datasets
- Use of augmentation and attention-based modules
- Integration with retina/iris for multi-modal systems
- Deployment as an Android-based mobile diagnostic tool

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