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Blood Group Identification from Fingerprints Using Convolutional Neural Network

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Abstract: Identifying blood groups usually means needles, labs, and waiting for biochemical results-resources that are not always available in emergencies or remote areas. This project introduces a non-invasive, intelligent alternative: predicting human blood groups directly from fingerprint ridge patterns and textures using a Convolutional Neural Network (CNN). By shifting the process from chemical analysis to biometric deep learning, we can classify fingerprints into the eight primary blood groups (A+, A-, B+, B-, O+, O-, AB+, AB-) almost instantly. We trained the CNN model on labeled datasets and integrated it into a responsive web interface built with Flask, HTML, and CSS. Users simply upload a fingerprint scan to receive an immediate prediction and confidence score. This system demonstrates how merging biometric analysis with deep learning can provide a rapid, preliminary screening tool, potentially saving critical time in resource-limited environments.

I. INTRODUCTION

Knowing someone's blood type matters in medicine, crime solving, plus border checks. Usually, doctors find it by testing real blood in labs, spotting how proteins react with antibodies. That way works well, yet needs needles, takes hours, relies on equipment and draws samples. Since faster, painless, smart ways are now wanted, scientists looked beyond blood itself. They began studying body traits you can measure - ones that might hint at what type flows inside. Few things stick around like fingerprints - everyone has them, they hardly change, yet hold intricate details worth exploring. Because machines now learn faster, spotting hidden structures in these swirls became possible through methods built on layered neural processing. These systems dig into fine textures, pulling out signals once invisible to older techniques. What showed up recently? A fresh use: guessing blood type just by reading ridge arrangements captured in an image.

Fingerprints possibly linking to blood types come up now and then in science work focused on human traits. Not long after birth begins, tiny ridges form under genetic instruction, shaped further by surroundings inside the womb. These skin designs stay through life, unique but maybe sharing hints about inherited biology. Blood markers like ABO or Rh run-in genes too, which keeps researchers comparing them with swirls and lines on fingertips. Instead of clear matches visible to eyes, weak trends appear only when large sets get analyzed. Machines trained to spot hidden details do better than people at catching slight shifts across thousands of samples. What looks random might carry faint signals tied to biology deeper than we once thought.

Nowadays deep learning pushes progress, so CNNs sit at the core of how computers sort images today. From fingerprints they pull layered details like ridges, tiny point clusters, directional trends, plus fine surface textures - all without human guidance. Instead of depending on fixed rules made by experts, these networks spot shapes straight from unprocessed pictures, improving step by step using error feedback loops. Their strength shows when guessing blood types from skin swirls since clues tied to ABO or Rh markers might hide in ways too subtle to describe by hand. Feed enough labeled examples - fingerprints matched to real blood results - and the system tunes itself to tell apart meaningful signs, splitting outcomes later into categories like O negative, AB positive, or others just based on texture traces.

Out in the real world, using a CNN to spot blood types brings clear benefits. Without needing any blood draws, the method skips physical intrusion entirely. Results appear before delays can build up. It costs less to do it this way because fingerprint sensors are cheap and already inside many phones, scanners, and locks. Since those tools exist everywhere, adding software that guesses blood type might help identify people more precisely during health emergencies.

Yet findings remain uncertain since links between finger patterns and blood types are just beginning to be explored. Though machines learn well, their results depend on how much good data they receive. Because differences in age or skin texture matter, images must capture a wide real-world variety. Even so, without broad samples including various ethnicities, systems might not work equally everywhere. Cleaning up data - removing noise, boosting ridges, cutting out sections, adjusting fingerprint angles - helps CNNs work better. Picking the right setup, whether it is VGGNet, ResNet, Inception, or something built from scratch, matters just as much. Fine-tuning settings behind the scenes pushes accuracy further than default choices ever could.

Still, even though using fingerprints to guess blood type avoids needles, it can expose private health details since people often give up their fingerprints just to log in somewhere. Because of this risk, any rollout needs clear rules shaped by law and ethics so personal data stays safe, preventing misuse when hiring, tracking, or deciding who gets coverage.

Even with hurdles, better deep learning systems keep drawing attention here. Promising classification outcomes show up often in papers using CNNs fed with fingerprints tagged by ABO and Rh types. More precise ridge examination helps too - along with reusing pre-trained networks, expanding data artificially, and mixing CNNs with classic biometric methods. Tiny but meaningful details matter now; some teams highlight them through focused attention layers or stacked model setups.

All things considered, figuring out blood type from fingerprints through Convolutional Neural Networks opens new paths in medicine, crime scene analysis, and access control. Fingerprint data sits everywhere these days - this method taps into that, using smart algorithms trained to spot subtle patterns without needing a drop of blood. Though it won't swap out lab tests just yet; it nudges us closer to backup systems where machines help guess medical details on the fly. Over time, with better training material and wider studies, these models might sharpen enough to speed up crisis care, upgrade identity checks, then quietly slip into health tech as one more layer of silent support.

II. MOTIVATION

From day one, this effort was shaped by problems tied to standard ways of spotting blood types - methods needing needle draws, labs, people with medical training. Such routines tend to drag on, cost too much, rarely reach remote clinics or urgent scenarios fast enough. When results lag, choices like giving blood during emergencies may go off track. Some skin-line research lately hints that whorls and loops on fingertips might link to inherited features including ABO or Rh factors. As machines learn better now - especially tools built like brain-inspired network layers - reading those tiny print details became doable without human eyes watching every curve. This idea came about because there's a real demand for speed, simplicity, and accuracy when figuring out someone's blood type - without needles or delays. Fingerprint pictures might hold the clues needed, analyzed through smart imaging tech built on convolutional neural networks. Mistakes made by people drop off sharply once machines take over pattern spotting. When every second counts, like during crises or accidents, waiting less means helping faster. Hospitals gain a first-check option, far-flung clinics get new reach, emergency teams find stronger footing - all using something everyone already has: their fingerprints.

III. WORKINGPRINCIPLE

The working principle of this project relies on biometric fingerprint analysis combined with a Convolutional Neural Network (CNN) to predict human blood groups. First, a fingerprint image is captured or uploaded through the web interface. The system carries out image preprocessing, which includes resizing, enhancing ridges, and segmenting to clarify the ridge patterns in the fingerprint image. These preprocessing steps make sure the image is standardized and ready for further analysis. After preprocessing, the CNN model processes the fingerprint image to automatically extract important features like ridge flow, minutiae points, texture patterns, and orientation fields. The CNN uses multiple layers, including convolutional layers, pooling layers, and fully connected layers to learn complex patterns in fingerprint images. The model then uses these learned features to classify the fingerprint into the correct blood group category with the help of activation functions and probability outputs. The trained model connects with a Flask-based web application, where users upload their fingerprint images. The backend server sends the image to the trained CNN model which analyzes the fingerprint features and predicts the most likely blood group along with a confidence score. The predicted result is then shown to the user through the interface, offering a quick, non-invasive, and automated way for preliminary blood group identification.

IV. LITERATURE SURVEY

Bharadwaj and Saraswati (1998) conducted one of the earliest dermatoglyphic studies exploring the relationship between fingerprint patterns and blood groups. Their research highlighted that the fingerprint biometrics, which analyses unique ridge patterns such as loops, arches, and whorls, can serve as a reliable biological marker due to their genetic stability over a lifetime. They observed statistical associations between specific fingerprint patterns and blood group types, laying the groundwork for biometric-based prediction systems in the future.[1]

Cummins and Midlo (1961) pioneers establishing the scientific basis for studying ridge patterns formed during fetal development. Their work emphasized that patterns are influenced by genetic and environmental factors, making them useful indicators for studying hereditary traits. This foundational research later supported studies attempting to correlate dermatoglyphic features with physiological characteristics such as blood groups.[2]

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Gupta et al. (2012) introduced automated fingerprint analysis using image processing techniques. Their work focused on extracting features such as ridge count, minutiae points, and orientation fields to classify fingerprints into blood group categories. Although their rule-based approach demonstrated moderate success, it was limited by its dependence on handcrafted features and sensitivity to image quality.[3]

Kumar and Patel (2015) further explored statistical methods by analysing ridge density and pattern distribution to predict Rh blood groups. Their hybrid approach combined statistical modelling with basic pattern recognition; however, the model struggled with low-quality or distorted fingerprint images, highlighting the limitations of traditional techniques.[4]

Singh et al. (2018) marked a transition toward machine learning by applying supervised classifiers such as Support Vector Machines and Random Forests. Using extracted texture features like GLCM and ridge frequency, their model improved prediction accuracy compared to earlier approaches. However, reliance on manual feature extraction still limited robustness and generalization.[5]

Rahman and Hossain (2020) expanded on machine learning approaches by implementing Naïve Bayes and k-Nearest Neighbour algorithms for fingerprint-based blood group classification. Their study achieved comparable accuracy levels but revealed that performance plateaued due to insufficient feature representation and variability in fingerprint acquisition conditions.[6]

Sharma and Das (2021) introduced Convolutional Neural Networks (CNNs) for fingerprint classification tasks. Their model leveraged deep learning to automatically extract hierarchical features from raw fingerprint images, eliminating the need for manual feature engineering. This approach significantly improved accuracy and demonstrated the effectiveness of CNNs in capturing complex ridge patterns and textures.[7]

Prakash et al. (2023) further enhanced deep learning performance by implementing a deeper CNN architecture combined with data augmentation techniques. Their study achieved over 90% accuracy, demonstrating the capability of CNNs to learn intricate spatial and textural relationships. However, their dataset was collected under controlled conditions, limiting real-world applicability.[8]

Thomas et al. (2024) explored hybrid models that combined CNN-based feature extraction with Gradient Boosting classifiers. Their approach improved classification performance and addressed issues such as class imbalance. This study highlighted the potential of integrating deep learning with traditional machine learning techniques for better results.[9]

Lee and Park (2024) investigated transfer learning approaches using pre-trained architectures such as VGG16 and ResNet50. Their work demonstrated that leveraging pre-trained models can significantly improve feature extraction and classification accuracy, although it requires substantial computational resources and large datasets.[10]

Devi and Rajan (2025) introduced Generative Adversarial Networks (GANs) for fingerprint image enhancement. Their research showed that improving fingerprint quality using GANs can significantly boost CNN-based classification accuracy, particularly in cases involving noisy or low-quality inputs. This advancement addresses one of the key challenges in real-world biometric systems.[11]

V. SYSTEM ARCHITECTURE

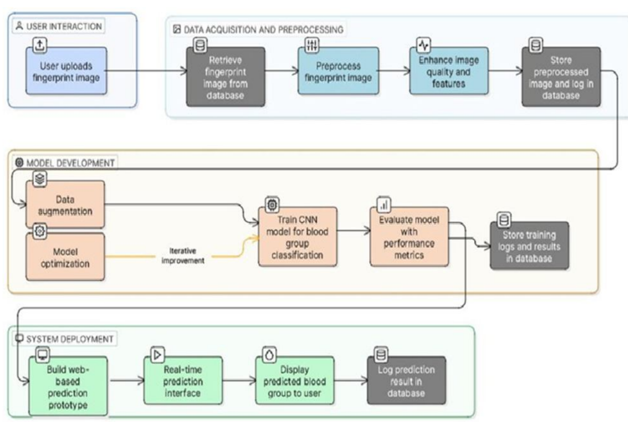

Fig1: -System Architecture

The system we are talking about is based on a website and a server that work together. This system is designed to find out what is in satellite pictures using a special kind of computer program. The system has a main part: a website that people can use a server that does the hard work, a part that looks at the satellite pictures and a place to store information if we need to.

When we use the system, we start with the website. We can get to the website using a web browser like we normally do. The website is made using things like HTML and JavaScript. On this website people can log in. Upload satellite pictures to be looked at. After the picture is uploaded the server gets a message to start working on it. The website also shows us the results in a way that's easy to understand.

The server is like the brain of the system. It uses a program to manage everything. First, it checks to make sure the person using the system is who they say they are. After that it gets the picture ready to be looked at by making it the right size and preparing it for the computer program. Then it uses a program called YOLOv8 to look at the picture and find things like farms, water and buildings.

When the program is looking at the picture it finds the things and draws boxes around them. After it is all done it cleans up the results so they make sense and puts them in a format that's easy to use. The results then go back to the website, where people can see them. This makes it easy for people to understand what the system found in the picture. The system can also store information if we need it to. This information includes things like who used the system, what pictures were looked at and what the system found. This helps us look at how the system is working and makes it easier to do things again if we need to. Overall, this system is a way to automatically look at satellite pictures. It combines a website with a powerful computer program and a place to store information. This makes it easy for people to upload pictures, find out what is in them and see the results in a way that makes sense. The satellite image analysis system is a tool for people who need to look at satellite pictures. The system is easy to use. Helps people understand what is in the pictures.

VI. METHODOLOGY

The proposed solution is founded on a Deep Learning-based Fingerprint Blood -Group Identification framework using Convolutional Neural Networks (CNN). This approach represents a paradigm shift from traditional laboratory-based blood typing to an automated, non-invasive, and rapid identification system. The core methodology can be broken down into three interdependent pillars:

A. Fingerprint Image Acquisition

The foundation of this system is built upon a curated, high-resolution fingerprint dataset rather than direct hardware acquisition. This stage is critical because CNN's ability to generalize depends entirely on the diversity and quality of the underlying data. We specifically selected labeled datasets that capture intricate ridge patterns, including key minutiae points like bifurcations and ridge endings, across all eight blood group categories. To ensure the model remains robust against real-world variability, the selection process prioritized images with varying orientations, pressure levels, and ridge densities. By utilizing a standardized digital dataset, we can maintain a consistent baseline for training while ensuring the raw input data is clean, normalized, and ready for deep learning analysis.

B. Image Pre-processing

After the fingerprint images are taken, they need to be cleaned up and made to look the same. First the background is. Then the brightness and contrast are made the same for all pictures. This helps the system see the parts of the fingerprint more clearly. Special filters are used to make the lines on the fingers look sharper and more continuous. Noise, which can be like static on a television, is also removed to make the pictures clearer. The pictures are also changed in ways like being turned or made bigger or smaller to help the system learn from them. All these steps make sure the pictures are good and the same. The system can find the important features.

C. Feature Extraction

This is the part where the system finds the information in the fingerprint pictures. The system uses a Convolutional Neural Network to do this. It looks at the pictures. Find the lines, the direction of the lines and the texture. As it looks deeper into the pictures it finds complex patterns, like how the lines flow and where the lines split. The system does not need to be told what to look for; it learns on its own. The features it finds are turned into numbers that the system can use to classify the fingerprints.

D. Classification Model

This is the part where the system uses the features to determine the blood group. The system uses a kind of model that is good at looking at pictures and finding patterns. The model has layers that help it learn and make decisions. It uses functions to help it learn complex patterns and to make sure it does not get too good at one thing and forget about others. The model is trained using examples of fingerprints and their corresponding blood groups. It is like teaching a child to recognize animals by showing them many pictures. The model gets better and better at recognizing the patterns in the fingerprints and predicting the blood group.

E. Blood Group Prediction

In this part the system uses the trained model to predict the blood group of fingerprints. The new fingerprint goes through the cleaning and processing steps as before. Then it is given to the model, which looks at the features and decides which blood group it belongs to. The system also gives a confidence score, which's like a percentage that shows how sure the system is of its answer. This helps the user know if the answer is reliable. This is the part where the system is actually used to predict blood groups. It is very fast and does not hurt.

F. Validation and Performance Evaluation

The final step is to make sure the system is working well and giving answers. This is done by comparing the predicted blood groups with the blood groups. The system is tested in different ways to make sure it is robust and works well even with poor quality fingerprints. This step is very important to make sure the system is reliable and can be used in real-life situations like in hospitals or for analysis. The Fingerprint Blood Group Identification system is a useful tool that can help people find out their blood group in a fast and non-invasive way. The Deep Learning-based system is the key to making this possible. The Fingerprint Blood Group Identification system uses Convolutional Neural Networks to make predictions. The Fingerprint Blood Group Identification system is an improvement over traditional method.

VII. DATASET

The database used in the project consists of a systematic and organized collection of fingerprint images that serve as the primary source of data for training and evaluating the Convolutional Neural Network model for the blood group classification. It forms the foundation of the proposed system, enabling the model to learn and recognize visual ridge patterns associated with different blood groups. This dataset is mainly divided into multiple categories, each corresponding to a specific blood type, ensuring a structured approach to classification. By maintaining a well-labeled and organized dataset, the system achieves consistency, reliability, and reproducibility in both training and evaluation processes.

A significant challenge in this domain is the absence of a standardized public dataset that directly links fingerprint images with blood group information. To address this limitation, the dataset for this project was developed through a controlled and institutionally supervised data collection process conducted within the college environment. This approach ensured that the data collected was relevant, accurate, and tailored specifically to the requirements of fingerprint-based blood group prediction. The controlled setting also allowed for better management of data quality and uniformity. Fingerprint images were collected from volunteer participants representing all eight major blood group categories: A+, A−, B+, B−, AB+, AB−, O+, and O−. Participation was entirely voluntary and based on informed consent. Each participant was clearly informed about the purpose of the study, and strict ethical guidelines were followed throughout the data collection process. To protect privacy, all biometric data was anonymized, and no personally identifiable information—such as names, roll numbers, or contact details—was recorded. Only the fingerprint images and verified blood group labels were retained for research purposes.

To ensure high-quality data acquisition, a standardized fingerprint capture process was followed. A high-resolution fingerprint scanner was primarily used to capture clear and detailed ridge and valley patterns, minimizing noise and distortions. In situations where a scanner was not available, an alternative method involving ink-based fingerprint impressions on white paper was adopted. These impressions were later digitized using a high-quality smartphone camera under controlled lighting conditions. All images were maintained at a resolution of approximately 300–600 DPI, ensuring sufficient detail for effective feature extraction using deep learning techniques.

The accuracy of blood group labels is critical for supervised learning; therefore, each participant's blood group was verified using authentic clinical records such as laboratory reports, medical documents, or blood donor identification cards. This verification process ensured the correctness of labels and minimized the risk of misclassification during model training. Once verified, the fingerprint images were systematically organized into folders based on their respective blood group categories, creating a clear and structured dataset hierarchy that facilitates easy access and integration into machine learning workflows.

To improve the robustness and generalization capability of the model, the dataset was designed to include natural variations found in real-world fingerprint acquisition. Multiple fingerprint samples were collected from each participant to capture differences in finger placement, pressure, orientation, lighting conditions, moisture levels, and sensor sensitivity. Incorporating such variations helps the CNN model learn more generalized patterns, making it more effective when handling unseen or imperfect fingerprint inputs in practical scenarios.

The dataset was developed exclusively for academic and research purposes and was securely stored within the institution's repository. Access to the dataset was restricted to authorized project members and faculty supervisors to maintain data security and confidentiality. Overall, the dataset reflects a carefully planned and ethically conducted collection process that emphasizes data quality, diversity, authenticity, and privacy. This strong data foundation plays a crucial role in ensuring the reliability and effectiveness of the proposed fingerprint-based blood group classification system.

Fig2:-Data Set Images

VIII. TECHNOLOGIES USED

The Automated Blood Group Detection System combines multiple technological elements which operate through its user interface and backend systems and machine learning capabilities to create accurate blood group detection results. The system uses HTML and CSS and JavaScript to create an interface which users can access through their devices. HTML establishes the basic structure which web pages use to display content on the homepage and upload page and result display page. CSS controls visual design to achieve correct page design and styling and device display compatibility. The interface uses JavaScript to create interactive elements which allow users to validate forms and handle image uploads and see results updates without needing to refresh the entire webpage. The system uses these technologies to create a user experience which provides both easy navigation and natural operation.

The system uses Python with the Flask framework to manage all of its server-side functions. Flask serves as a compact and adaptable web framework which developers can use to create web applications with maximum efficiency. The system manages user authentication processes through login and signup functions while it handles HTTP requests and processes uploaded fingerprint images. The backend system connects the user interface with the machine learning model by processing input images and forwarding them to the prediction engine which generates results for the frontend display. Flask provides simple machine learning library integration which makes it an ideal platform for creating AI-powered applications.

The machine learning system uses deep learning frameworks like TensorFlow and Keras and PyTorch to build and educate the Convolutional Neural Network (CNN) model. The frameworks enable users to construct neural network designs and conduct numerical operations and execute machine learning tasks. The frameworks deliver essential components which enable developers to construct neural network models while conducting mathematical computations and enhancing their system performance.

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Keras serves as a high-level application programming interface which works with TensorFlow to help users build convolutional neural network components through its simplified design process for convolutional and pooling and fully connected layers. PyTorch enables users to create custom models through its dynamic computation graph system which provides them with complete control over their experimental work. The technologies support CNN model training and validation and deployment processes which results in precise blood group classification outcomes.

The implementation of image processing techniques depends on OpenCV and NumPy libraries which serve essential functions during the data preprocessing stage. OpenCV performs multiple functions which include image resizing and image normalization and noise reduction as well as fingerprint ridge pattern enhancement. NumPy enables users to perform numerical calculations and handle array data which they need for model input and preprocessing activities. The tools standardize fingerprint images before processing which helps the CNN model make better predictions of results.

The system operates as a web application which combines all system components into one complete technological framework. The frontend uses HTTP requests to connect with the Flask backend while the backend uses the trained CNN model to produce predictions. The system processes fingerprint images in real time while instantly showing results to users. The system combines web development tools with deep learning frameworks which allows it to maintain user-friendly design and high performance and system expansion capabilities that make it useful for healthcare and biometric research.

A. Result User Interface Page

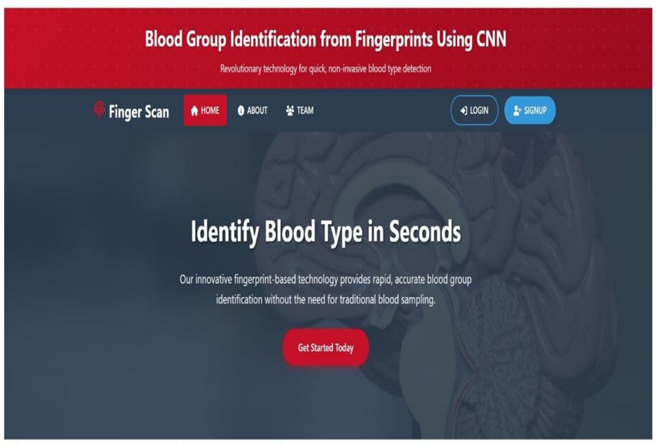

Fig3: Home Page

B. Register Page

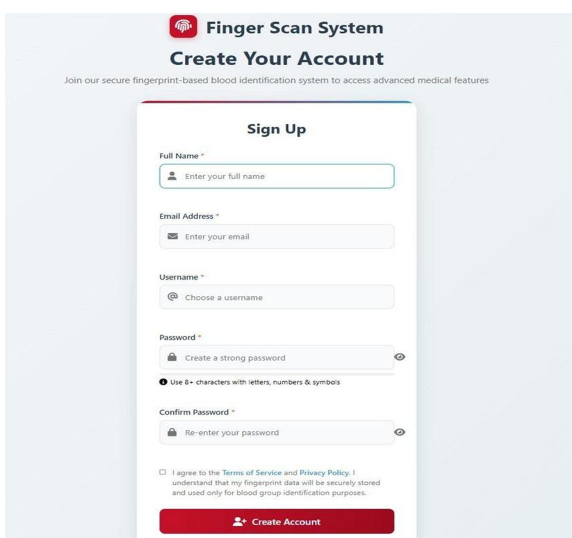

Fig4: Register Page

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C. Login Page

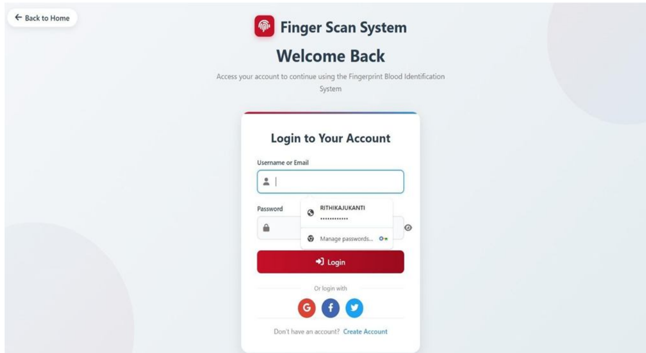

Fig5: User Login Page PREDICTION PAGE:

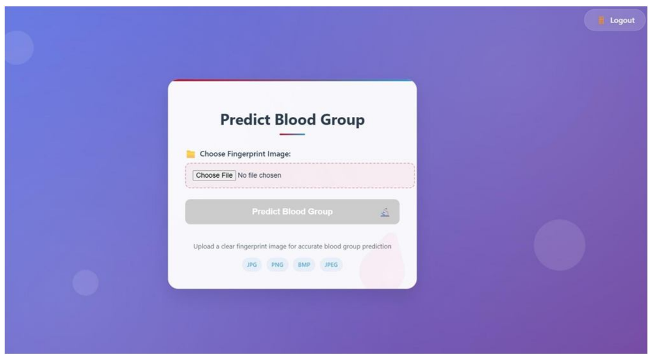

Fig 6: Image Selection Page

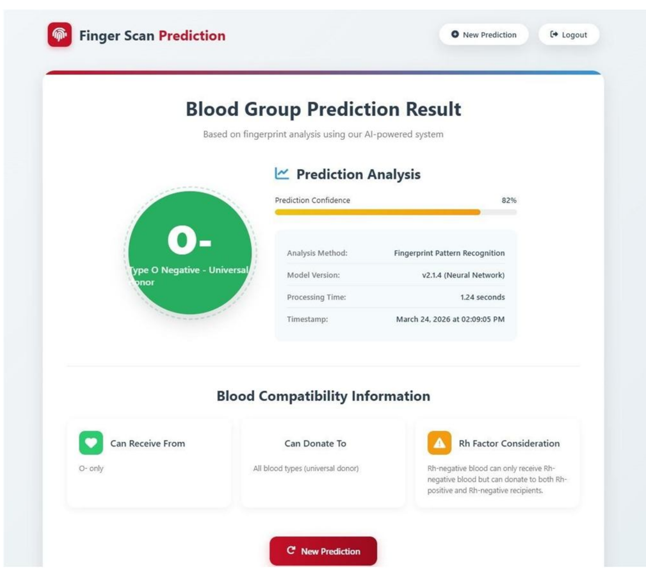

Fig 7: Prediction and Segmentation Page

IX. FUTURE SCOPE

This project will develop a fingerprint-based blood group prediction system which will become more reliable and scalable and applicable to actual situations. The research aims to improve model performance by expanding the dataset through fingerprint sample collection from people who belong to different age groups and genders and ethnicities. Advanced deep learning architectures like ResNet and MobileNet and EfficientNet will provide better classification results together with decreased computational demands.

The system will become more usable for hospitals and clinics and emergency services because cloud platform deployment will enable them to access the system in real time. The system requires large-scale clinical trials and medical validation studies to demonstrate its ability to meet healthcare standards and obtain medical facility acceptance.

The system requires further development work which will enhance its existing features while boosting its security measures and user experience. The application will develop into a complete healthcare support system through the addition of patient registration and authentication and medical history tracking features. The implementation of strong security measures together with data protection mechanisms will become essential for protecting sensitive biometric and medical information according to healthcare regulations. The development of a mobile application version can further improve accessibility, particularly in remote or resource-limited settings where quick diagnostics are required. The system will become more user-friendly through interface and experience design improvements which will enable users to navigate the system through better engagement.

X. CONCLUSION

The project demonstrates fingerprint images as a non-invasive accessible method for blood group prediction through the implementation of Convolutional Neural Networks and current web technologies. The system built by developers combines image preprocessing and deep learning classification with a Flask web interface to deliver complete end-to-end functionality. The CNN model developed through a comprehensive training and evaluation process demonstrates its ability to learn distinct fingerprint patterns which it uses to accurately determine blood group categories.

The system demonstrates artificial intelligence applications which improve medical diagnostics through its ability to quickly and contact-free assess blood groups. The model serves as an additional testing solution which proves useful for emergency medical situations and remote healthcare environments and resource-limited facilities despite its design not to replace laboratory serological testing. The project establishes multiple pathways for future development because it supports dataset growth and deep learning model development and mobile platform deployment for immediate field applications.

The project work demonstrates that using biometric imaging together with deep learning results in effective diagnostic solutions. The project establishes a vital foundation which will enable medical support systems to become more intelligent and faster and easier to access.

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