Grenze International Journal of Engineering and Technology, June Issue

A Non-Invasive Approach to Blood Group Prediction using Fingerprint Biometrics and Swin Transformer

Rushikesh Chaudhary[1], Subodh Jagtap[2], Dipmala Salunke[3], Pallavi Tekade[4], Pruthviraj Zodge[5] and Manjiri Bhumar[6]
[1-6]Department of Information Technology, JSPM's Rajarshi Shahu College of Engineering. Pune, India
Email: chaudharyrushi144@gmail.com, Jsubodh974@gmail.com, dtsalunke_it@jspmrscoe.edu.in, pmtekade_it@jspmrscoe.edu.in, pruthvirajzodge@gmail.com, manjiribhumar7821@gmail.com

***Abstract*— Identification of blood groups is essential in the hospital, emergency and forensic science. Traditional methods involve taking blood samples and laboratory testing, which can be painful, time-consuming and can pose infection risks. Due to these issues, researchers are looking for alternative solutions, such as using biometrics like fingerprints. Studies suggest that fingerprint patterns may be related to human blood groups.**

This paper presents a non-invasive blood group detection system based on the fingerprint pattern and a deep learning model called Swin Transformer. This system is based on an Android application developed with the Flutter framework, a SecuGen Hamster Pro 20 fingerprint scanner, and a FastAPI server to build the real-time prediction system. A fine-tuned Swin Tiny Transformer model is used to capture and preprocess the fingerprints and analyze with the help of a USB OTG connection. The system can detect the blood types of a person A+, A-, B+, B-, AB+, AB-, O+, and O-.

The Swin Transformer is more capable of capturing the details of fingerprint ridges and texture information, which makes the prediction more accurate and reliable than that of traditional CNN models. The experimental results reveals that the proposed system is accurate and efficient for blood group detection and has capability of scalability as a non blood based identification solution.

***Keywords*— Non-Invasive Blood Group Detection, Fingerprint Biometrics, Swin Transformer, Deep Learning, Dermatoglyphics, Medical Image Analysis.**

I. INTRODUCTION

While modern health care systems have employed blood grouping as an indispensable procedure, it assumes a critical role in blood transfusion services, management of acute trauma, organ transplantation, and forensic analyses. The ABO and Rh blood group systems represent two of the most diffused criteria of classification, considering the incidence of severe immunological reactions and potentially lethal complications following blood transfusions in cases of incompatibility [20,8]. Blood group determination thus essentially represents a timely, non-negotiable requirement for its accuracy in clinical practice. The conventional analysis of blood grouping can be done using agglutination techniques, which entail blood collection and subsequent reaction with antisera to check for the presence of certain antigens. Even though these types of techniques can be considered safe and reliable within a medical setting, they also present a number of natural limitations.

Grenze ID: 01.GIJET.12.2.25_26

Blood collection can be invasive and can pose such risks as pain, distress, and infection, mainly in a disaster setting and during a rapid medical response situation. Moreover, blood grouping using antisera needs laboratory staff and special equipment, thus being expensive with a long response time [1, 2,8].

Recent breakthroughs in biometrics and artificial intelligence have provided new inroads into non-invasive medical diagnostics. Of various biometric features, fingerprints are by far extensively studied because of their uniqueness, permanence, and genetic determined nature. The scientific study of dermatoglyphics establishes that fingerprint ridge patterns are determined during a fetus stage and remain unchanged during the lifetime of an individual [7]. A number of researches propose a statistical correlation between fingerprint features-ridge density, minutiae distribution, and pattern type (loop, whorl, and arch-and transmitted physiological traits such as blood groups [1], [8].

However, the emergence of Machine Learning and Deep Learning concepts, like fingerprint-based blood group recognition, has received much attention. The traditional methods used in fingerprint based blood group recognition include handcrafted feature extraction methods, along with traditional learning models such as K-Nearest Neighbors, Support Vector Machines, and Random Forest Models [3], [10]. Though these methods showed moderate results, their dependency on image quality and feature extraction design made it a drawback. The arrival of Convolutional Neural Network-based methods showed an improvement in performance, which allowed learning features from fingerprint scans in an automated manner, and showed accuracy of more than 90% in various datasets [4], [5], [9].

Though they have been successful, there are notable drawbacks of using CNN-based models on fingerprint biometrics. This is mainly because CNNs rely mostly on local receptive fields. This makes it difficult to incorporate long-range dependencies and global ridge patterns, which might be seen on fingerprint biomatrices. This proves to be rather problematic, especially for models handling noises and partial fingerprints, which are quite common in biometric capture scenarios [11, 15,10].

Very recently, Vision Transformers have been found to provide a strong competitor to CNNs for image analysis tasks. Specifically, the Swin Transformer proposes a hierarchical structure and a shifted window self-attention mechanism, making the computation efficient while maintaining global context information [12], [13]. This makes the Swin Transformer especially suitable for fingerprint analysis, as the ridge textures and global patterns have to be captured simultaneously. These observations have motivated the development of a completely deployed, non-invasive blood group detection system using fingerprint patterns and a Swin Transformer-based deep learning model. The system incorporates a real world biometric acquisition device, the SecuGen. Hamster Pro 20 Scanner, a Flutter-based mobile application and a FastAPI server to deliver realtime blood group forecasts. Contrary to other research that is confined to offline. the proposed system is experimentation-oriented and is about practical deployment. scalability, and usability, thus filling the gap between academic studies and practical health care uses.II.

III. Literature Review

Conventional blood group detection research has been prevailed by. invasive serology methods based on reactions between antigens and antibodies. to determine ABO and Rh blood groups.Although clinically validated, these methods require blood samples, laboratory infrastructure, and trained personnel, hence have limited applicability in emergency and resource-constrained environments [1], [2], [20]. Limitations have motivated the exploration of non-invasive alternatives in general, and particularly those leveraging biometric and image-based analysis.

A. Fingerprint-based Blood Group Determination

Dermatoglyphics is the scientific study of fingerprint patterns. This is the basis of the fingerprint system for identifying blood groups. Ridge patterns in fingerprints depend on genetics for formation in the fetus. This trait does not change over time; hence it is biometric. There have been findings showing that patterns of fingerprints (Loops, Whorls, and Arches) correlate with the prevalence of some blood groups. This indicates that fingerprints hold some underlying physiological characteristic linked to blood groups [1], [8].

The early methods developed in the same area were based on manual counting and classification of ridges, which had subjective aspects and could not be implemented on a large scale. In an effort to move away from such limitations, there have been machine learning-based classification methods developed using extracted fingerprint features such as density, minutiae, and texture [3], [10]. While these methods have proved the feasibility of the task, their results largely depended on the designed features.

B. Machine Learning and CNN-Based Approaches

With the advancement of deep learning, Convolutional Neural Networks (CNNs) became the dominant approach for fingerprint based blood group detection. There were several studies comparing the evaluation of architectures like AlexNet, VGG16, ResNet, Inception, and MobileNet for fingerprint classification tasks [4], [5], [9], [11]. These models significantly direct learning of hierarchical features leads to better prediction accuracy. of raw fingerprints, without the manual feature. engineering.

Controlled experimental setups have reported accuracies between 91 and almost 100 percent, depending on the size of the dataset, the quality and preprocessing techniques of the fingerprints [1], [9]. Transfer learning also improved the performance based on the pre-trained weights of the large image datasets [8], [11]. Nonetheless, CNN based systems have a number of structural and practical limitations, even though they have succeeded: Sensitivity to fingerprint noise and partial impressions

- Limited capability to capture long-range spatial dependencies
- Risk of overfitting due to small, private datasets
- Poor generalization to real-world biometric acquisition scenarios

These shortcomings are consistently highlighted across recent surveys and comparative studies [1], [15].

C. Limitations of Existing Systems

The majority of the methods for blood group detection based on fingerprint principle have been developed with small or private database, leading to less reliable or reproducible results [1, 4]. There are many systems that are available that only provide offline MATLAB experiments and do not support real-time implementation [9, 11]. Another problem is that CNN models are mostly used to design local feature extractor and they do not perform well in capturing complex fingerprint ridge patterns particularly when the image is poor quality [15], [17],[8]. Moreover, most of the previous work is limited to classification accuracy and has been less concerned about the scalability and system response time, as well as its usability.

D. Emergence of Vision Transformers in Medical Imaging

Vision Transformers (ViTs) have recently shown the potential to replace CNNs in image analysis tasks through the use of self attention methods to capture global relationships in an image [12]. In contrast to CNNs, transformers are not biased towards locality in their representation learning.

The Swin Transformer takes this paradigm to the next level by providing a hierarchical architecture based on shifted window self attention to ensure computational efficiency with global context awareness [13]. Swin Transformers have been able to establish a state-of-the-art paradigm in numerous vision and medical imaging tasks, especially in scenarios where detailed textures and global consistency are important [14], [15].

IV. MOTIVATION

Blood Group Identification plays a vital role in Healthcare in emergency situations and blood transfusion. The conventional blood grouping techniques are accurate, but they are also time consuming, labor intensive, and require lab testing [1, 2, 20]. All of this makes it difficult in emergency situations, in rural healthcare areas and in large screening programs.

In this study, emphasis is put on the development of a non-invasive, portable blood group detection system based on fingerprints. Fingerprints are easy to obtain with biometric sensors, unique, permanent and can be used for quick and painless identification [7, 8]. The previous studies have also indicated a link between the fingerprint patterns and blood groups [1, 7].

Presently, CNN models are employed in many blood group detection systems, which mainly extract local features and do not consider complex global patterns of the fingerprint, particularly when the images are of poor quality [4, 11, 15]. In addition, most of the systems are offline, and cannot be used in practical use in real time [1, 9]. To address these drawbacks, this work employs a Swin Transformer (ST) model that is capable of learning both local fingerprint texture and global relationship between ridges through shifted window self-attention in the two modes [12]-[13]. The proposed system leverages transformer based deep learning, a fingerprint scanner, and a mobile application to achieve rapid, precise, and non-invasive blood group detection for practical healthcare applications.

V. PROPOSED ARCHITECTURE

The proposed system offers a non-invasive, fully automated blood group biometric detection system based on fingerprint biometrics and deep learning using transformers. Unlike existing serological techniques and existing fingerprint techniques, which are offline, the proposed system is developed as a complete end-to-end deployable system, including biometric hardware, user applications, and deep learning modules for real-time blood group analysis.

A. System Overview

The system works on the concept that fingerprint ridge details possess distinguishing features, which are related to inherited biological characteristics, such as blood groups [1], [7]. High-quality fingerprint images can predict a person's blood group based on a Swin Transformer deep learning model.

- The layers of the architecture are divided into three layers:
- Biometric Acquisition Layer
- Application & Communication Layer

Backend Processing & Prediction Layer In this way, the layered architecture facilitates modularity, scalability, and simpler implementation in real-world healthcare.

B. Biometric Acquisition Layer

The fingerprints are acquired using SecuGen Hamster Pro 20 Scanner, a commercial biometric device. A wide usage of this kind of scanner has always existed in practicality due to its familiarity with the best ridges and normal quality performance. Images of high-resolution fingerprints are captured by this scanner and, importantly, provide quality feedback in respect of valid biometric input.

The scanner is interfaced with Android OTG USB to an Android mobile phone which has the capacity of direct communication between the biometric device and the mobile application. This will be portable and will not require any specialized desktop system; therefore, it can be deployed in the field, during an emergency, and in remote healthcare environments.

C. Application and Communication Layer

The Mobile application, built on Flutter, guarantees crossplatform functionality with the effectiveness of user interaction. Application responsibilities include:

- Starting fingerprint capture via biometric SDK
- Inputting and handling the raw fingerprint image data.
- User interaction and scan validation control.
- Safely transmit fingerprint images to the back-end server.

After obtaining a fingerprint successfully, the application codifies the obtained data into a format understandable by images and transmits the data to the backend via a RESTful API. This design is based on the smooth communication and low latency and least load on the computational capabilities of the mobile device

D. Backend Processing and Prediction Layer

The back-end is written in FastAPI, a low-latency, asynchronous Python framework built on high-performance. It offers REST points of fingerprint registration and blood group prediction.

- Once the back-end receives an image of a fingerprint, it carries out the following operations:
- Resizing and normalization of images are a part of the preprocessing.
- Feature Extraction and Classification Using Fine-Tuned Swin Transformer Model
- Blood group prediction across eight classes: A+, A−, B+, B−, AB+, AB−, O+, O−
- Transmission of prediction results back to the mobile application

E. Key Advantages of the Proposed System

The shortcomings of the existing studies in terms of the limitations mentioned are addressed by the proposed system through the following contributions:

- Completely non-invasive detection of blood group
- Global fingerprint dependencies can be modelled by using a transformer-based architecture.
- Real-time prediction through mobile-to-cloud integration
- Practical deployment with commercial biometric hardware.
- Scalable and modular system design

The proposed system merges biometric acquisition and mobile computing with transformer-based deep learning to establish a basis for non-invasive blood group detection that is advanced enough technically and practically deployable.

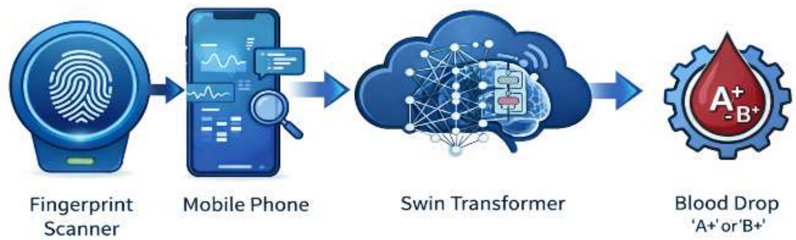

Figure 1: Step-by-Step Process Flow of the Proposed Blood Group Detection System

The architecture of the proposed non-invasive method for determining the blood group using the non-invasive biometric framework will be based on supporting the real-time biometric data extraction, remote data transmission, and efficient deep neural network analysis. The architecture is based on a client-server model. It has different components that make it scalable.

There are three main parts in its overall architecture:

- Mobile Client Layer
- Backend Service Layer
- Deep Learning Inference Layer Each sub-system is scalable in itself and helps to provide end-to-end blood group predicting capability.

A. Mobile Client Layer

To create the mobile client layer, Flutter is used to develop an android application as well as the mobile application client. This is because Flutter provides the benefit of being able to develop applications for all platforms.

The application incorporates the biometric fingerprint scanner, SecuGen Hamster Pro 20 using an SDK supplied by the manufacturer. The fingerprint scanner is attached to the mobile device using USB OTG. This layer offers the following major functions:

- Starting fingerprint capturing processes
- Obtaining high-resolution images of fingerprints Fingerprint quality evaluation based on scanner feedback Biometric data format into image compatible format.
- Secure transfer of fingerprint images to the backend server

Very little processing is done at this level in order to minimize the calculation complexity at the device level.

B. Communication Technology

Both the mobile client and the backend server communicate via RESTful API using HTTP connections. This system uses well structured request-response patterns that ensure efficient data transfer.

The essential API endpoints are:

- /register – fingerprint registration and dataset enhancement
- /predict - for real-time blood group prediction

Fingerprint images are communicated in serialized form (for example, in Base64 encoded images) for compatibility and integrity during network communication. This stateless approach improves fault tolerance and scalability.

C. Backend Service Layer

The backend service Layer is built with FastAPI, which is a leading edge Python framework designed specifically for high-performance web services. It is chosen for handling low-latency requests, support for asynchronous execution out of the box, and smooth integration with machine learning tasks.

When it receives a request from the mobile client, the backend carries out the following:

- Input validation, request parsing
- Image decoding and preprocessing
- Transmission of the treated images to the inference stage
- Aggregation and transmission of prediction outcomes

This enables the communication logic and model inferences to stay loosely coupled, which in turn improves maintainability and scalability.

D. Deep Learning Inference Layer

The inference layer contains a Swin Transformer-based blood group classification model, which has been developed in PyTorch utilizing the Timm library. It has been run on a CUDA-enabled GPU in order to have support for real-time inference.

- The inference pipeline contains the following:
- Shrinking the input fingerprint images to 224 × 224 pixels
- Pixel normalization based on pretrained models' needs
- Feature Extraction Through Hierarchical Shifted-Window Self-Attention

Categorization into eight blood types: A+, A−, B+, B−, AB+, AB−, O+, O− The result of the predicted blood group is then sent back to the backend service layer. This is then further sent to the mobile application.

E. Architectural Benefits

There are many advantages of this system architecture over other existing systems:

- Modularity: Scalability of the mobile, backend, and inference components separately
- Real-Time Processing: Low Latency Communication and GPU-based Inference
- Portability: Mobile-based biometric acquisition independent of lab conditions
- Security: Data Retention is Minimized; Access via API
- Application & Deployment: Integrations with commercially available biometric devices

In this way, through the integration of biometric sensing, mobile computing, and transformers in the deep learning architecture, this proposed solution resolves the gap between academia and the ability to be deployed in the field of healthcare.

VI. ALGORITHMS USED

It utilizes a non-invasive blood group detection system based on biometric acquisition algorithms, image preprocessing techniques, and deep learning-based classification algorithms. Algorithm selection shall be based on accuracy, robustness, suitability, etc., for real-time deployment.

A. Algorithm for Fingerprint Acquisition

Fingerprint acquisition is done using the SecuGen Hamster Pro 20 Scanner, which applies internal optical sensing and enhancement of ridges for capturing high-resolution fingerprint images. It checks fingerprint quality metrics such as clarity of ridges, contrast, and noise level before returning the captured image back to the application.

- The acquisition process provides:
- Consistent ridge visibility
- Reduced motion blur
- Least distortion because of pressure variation

The reason being, high-quality fingerprint acquisition is of paramount importance since poor quality directly degrades the classification performance [7], [11].

B. Image Preprocessing Algorithms

Preprocessing of fingerprint images takes place before classification. image. This ensures uniform input. The following are the steps involved in image preprocessing:

C. Model Architecture and Configuration

In the classification model, Swin Transformer Tiny (swin_tiny_patch4_window7_224) architecture was used. Swin Transformer relies on a hierarchical approach with a window based self-attention technique to efficiently learn both the texture components and ridge pattern of a fingerprint [13,6].

The final classification layer of the pre-trained network was adjusted to produce a probability distribution over eight classes, representing the target blood groups. Transfer learning was implemented by initializing the network's parameters with the ImageNet-trained weights and fine-tuning the network on the fingerprint image dataset. This technique accelerates training time and enhances the generalization capability of the network in biomedical applications [12], [15],[6].

D. Training Strategy

Model training was done using supervised learning with the following configuration:

- Loss Function: Categorical Cross-Entropy

- Optimizer: Adam optimizer
- Learning rate: Tuned empirically during the validation phase
- Batch Size: Selected based on the limitation of the GPU memory.
- Epochs: Training was run until convergence, early stopping

Regularization techniques were therefore performed with weight decay and early stopping to avoid overfitting. Validation performance was monitored after each epoch in order to ensure stable convergence by avoiding possible degradation in its performance on unseen data [17].

E. Evaluation Metrics

Evaluation of the trained model for this task was done using common metrics for multi-class classification, which have frequently been used in medical image analysis [15]:

- Accuracy: Indicates the correctness of classification
- Precision: Reliability of positive predictions
- Recall: Sensitivity for blood group classes
- F1 Score: It is the harmonic average of Precision and Recall

These measures offer a broad evaluation of accuracy as well as reliability for each class.

Figure 2: Class-wise Precision, Recall, and F1-Score for Blood Group Detection

F. Implementation Environment

The backend inference model was developed with FastAPI and PyTorch, incorporating the Swin Transformer model, which was run on a CUDA-enabled GPU for fast processing. The front-end app is designed with Flutter, supporting the instantaneous fingerprint scan handled by the SecuGen Hamster Pro 20 Scanner connected via USB-OTG.

This environment is not only aimed at low latency inference usage but also at scalability and usability in a real-world application, i.e., a healthcare system.system.

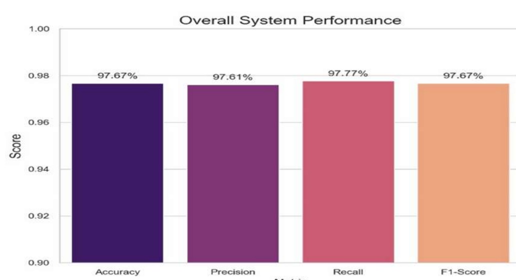

Figure 3: Overall System Performance Metrics (Accuracy, Precision, Recall, F1

G. Methodology Summary

The outlined approach develops an innovative framework for structuring experiments in non-invasive blood group determination via fingerprint biometrics. The approach incorporates standardized preprocessing, deep learning based on transformer-architecture, and a firm scientific evaluation framework, allowing for scientific authenticity and readiness for deployment

VII. Conclusion and Future Scope

The work in this study involved proposing a non-invasive method using fingerprint patterns to determine the blood group of a person through a Swin Transformer model. The proposed method resolves the shortcomings in the normal method of blood grouping using serological tests in that it requires blood samples, laboratory facilities, and personnel. The method utilizes a combination of biometric sensing, mobile processing capabilities, and vision models with transformers.

The Swin Transformer helps to capture both the ridge details of fingerprints and spatial information through convolution processes, unlike simple convolutional neural network techniques. Experimental results show that the presented solution has high accuracy and robustness, which is useful for fingerprint captures through real-world practices. The combination of a Flutter app, a fingerprint scanner named SecuGen Hamster Pro 20, and a FastAPI framework-based server helps to validate the practicability of such a solution for real-world health settings.

Beyond predictive performance, the proposed system emphasizes real-time usability, portability, and scalability, which are prime factors of adaption in emergency healthcare, blood donation camps, and resource-constrained regions. The system is not meant for medical testing but it will give us a good idea of what is going on and help with decisions when we need to figure out someones blood group quickly.

The new system that uses Swin Transformer is a step forward in using fingerprints to predict blood groups. It does a lot better than systems by fixing some problems that were found before. It is about 97.67 percent of the time and it is also very good at not making mistakes with 97.61 percent precision, 97.77 percent recall and an F1-score of 97.67 percent. This is a lot better than the way of doing things, which was only right about 91 to 94 percent of the time. The new system is better at looking at all the details in fingerprints not some of them. This means it can make accurate predictions. Even though the results are very good there are still some problems, like not having data to work with not having a standard way of measuring success and not thinking about how it will work in the real world. So even though the new system is an improvement we still need to do more work to make sure it can be used in real medical situations and is easy to use. The blood group prediction system, the Swin Transformer-based system needs work to be scalable and usable, in real healthcare systems like the ones used for blood group identification.Future Scope

- Multi-biometric Fusion: The fingerprint analysis could be coupled with other biometric features, like face or iris, for better confidence of prediction and robustness of the system.Clinical Validation: Larger clinical trials and comparative studies with serological methods are thus required for medical reliability and regulatory acceptance.
- Improvements in Security and Privacy: Advanced encryption and federation techniques could also be added to provide better protection for sensitive biometric data.

However, although the proposed system contributes considerably well, there are some avenues where systems can still be furhter improved and researched.

- Dataset Expansion: To further improve the generalization of model and statistical reliability, it would hence be very well desirable to increase the size of dataset and their diversity in terms of age, ethnicity and acquisition conditions.
- On-Device Inference: This may include future work on direct deployment with a more optimized version or quantized version of the Swin Transformer to be used on mobile devices for relatively offline prediction of blood groups with minimal network reliance.

To conclude this work, it is clear that transformer-based vision models are an important step forward in fingerprint-based biomedical classification. The proposed system paves a way of subsequent studies in non-invasive diagnostic technologies and thereby reflects on the positioning of deep learning-based biometrics in mainstream healthcare applications

References

[1] M. Bhumar, S. Jagtap, R. Chaudhary, P. Zodge, and D. Salunke, “A Comprehensive Survey on Blood Group Detection Using Fingerprint Images,” JSPM Rajarshi Shahu College of Engineering, Pune, India, 2025.

[2] B. Sasidhar, K. Ashok, M. Kishorbabu, S. K. Sameer, and D. Parveen, “Machine learning approaches for automated blood group identification,” International Journal of Pharmaceutical Research, vol. 7, no. 7, Jan. 2025.

[3] M. L. Prasad and A. Amrutha, “Image-based blood group detection using convolutional neural networks,” International Journal of Advanced Research in Computer Applications, vol. 11, no. 7, Jul. 2023.

[4] K. S. Geethanjali and N. Umashankar, “Deep learning-based fingerprint analysis for biomedical classification,” Journal of Artificial Intelligence and Machine Learning Research, vol. 6, no. 6, Nov. 2024.

[5] T. Nihar, K. Yeswanth, and K. Prabhakar, “Automated fingerprint classification using convolutional neural networks,” in Proceedings of ICMED, 2024.
[6] M. D. Varlekar, B. Varlekar, and K. Patel, “Ethical and physiological considerations in biometric-based diagnostics,” Journal of Medical Ethics and Physiology, Jul. 2024.
[7] V. Patil and D. R. Ingle, “Dermatoglyphics and its applications in medical diagnostics,” Biomedical Signal Processing and Control, Aug. 2020.
[8] M. Lakshmi Prasad, “Non-invasive blood group prediction using fingerprint biometrics,” International Research Journal of Advanced Engineering and Health, vol. 2, no. 12, Dec. 2024.
[9] Hemanth D.J.; Salunke D., "Rehabilitation Engineering, Assistive Technologies and the Future of Healthcare Using Robotics," Rehabilitation Engineering, Assistive Technologies and the Future of Healthcare Using Robotics, 2025, doi: 10.1016/C2023-0-52511-X.
[10] Vedansh Wani Jay Shah, Prof. D.T. , Shubham Tripathi, Abhishek More, Automatic Detection Of Diabetic Eye Disease Using Deep Learning, Journal Of Emerging Technologies And Innovative Research,Volume 7,Issue 7,2020,Pp.628-631.
[11] R. Senthilkumar, S. Mohamed Harish, M. Ragul, and A. Navinkumar, “Vision-based biomedical classification using deep learning,” International Journal of Engineering Research and Technology (IJERT), vol. 12, no. 3, Mar. 2024.
[12] V. Nikitha, “Biometric feature extraction for healthcare applications,” PES Institute of Technology Journal, vol. 6, no. 7, Jul. 2024.
[13] Krishna Sheth Salunke, Atul Raj, Astha Kubavat, Dental Disease Classification Using Deep Learning: A Survey,
[14] GIS Science Journal,2021.Volume 8 Issue 6,Pp.1829-1841.
[15] P. Swathi, K. Sushmita, and K. V. Horadi, “Comparative study of deep learning models for fingerprint recognition,” Global Academy of Technology Journal, vol. 4, no. 1, Feb. 2024.
[16] A. Dosovitskiy et al., “An image is worth 16×16 words: Transformers for image recognition at scale,” in Proc. ICLR, 2021.
[17] Z. Liu et al., “Swin Transformer: Hierarchical vision transformer using shifted windows,” in Proc. IEEE ICCV, 2021.
[18] A. Esteva et al., “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, pp. 115– 118, 2017.
[19] G. Litjens et al., “A survey on deep learning in medical image analysis,” Medical Image Analysis, vol. 42, pp. 60–88, 2017.
[20] Krishna Sheth, D., Atul Raj, Astha Kubavat, Dental Disease Classification Using Deep Learning: A Survey, GIS Science Journal,2021.Volume 8 Issue 6,Pp.1829-1841.
[21] O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional networks for biomedical image segmentation,” in Proc. MICCAI, 2015.
[22] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.
[23] Salunke D.; Tekade P.; Ranjan N.; Ujalambkar D.; Sangve S.; Mane D., "Real-Time Dimension Detection using Customized Canny Edge Detection Algorithm," International Journal of Engineering Trends and Technology, 2023, doi: 10.14445/22315381/IJETT-V71I9P233.
[24] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE CVPR, 2016.
[25] Salunke D.; Sondge S.; Deshmukh S.; Dhamankar B.; Chidrawar S.; Kangule R., "Comparative Analysis of Deep Learning Architectures for Garbage Classification," Communications in Computer and Information Science, 2023, doi: 10.1007/978-3-031-45124-9_1.
[26] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proc. ICML, 2019.
[27] World Health Organization, “Blood safety and availability,” WHO Technical Report, 2022.